BEAT: A Large-Scale Semantic and Emotional Multi-Modal Dataset for Conversational Gestures Synthesis

Haiyang Liu¹ Zihao Zhu² Naoya Iwamoto³ Yichen Peng⁴ Zhengqing Li³ You Zhou³ Elif Bozkurt⁵ Bo Zheng³

The University of Tokyo
 Keio University
 Huawei Technologies Japan K.K.
 Japan Advanced Institute of Science and Technology
 Huawei Turkey R&D Center



Fig. 1. Overview. BEAT is a large-scale, multi-modal mo-cap human gestures dataset with semantic, emotional annotations, diverse speakers and multiple languages.

Abstract. Achieving realistic, vivid, and human-like synthesized conversational gestures conditioned on multi-modal data is still an unsolved problem, due to the lack of available datasets, models and standard evaluation metrics. To address this, we build Body-Expression-Audio-Text dataset, BEAT, which has i) 76 hours, high-quality, multi-modal data captured from 30 speakers talking with eight different emotions and in four different languages, ii) 32 millions frame-level emotion and semantic relevance annotations. Our statistical analysis on BEAT demonstrates the correlation of conversational gestures with facial expressions, emotions, and semantics, in addition to the known correlation with audio, text, and speaker identity. Based on this observation, we propose a baseline model, Cascaded Motion Network (CaMN), which consists of above six modalities modeled in a cascaded architecture for gesture synthesis. To evaluate the diversity of synthesized gestures, we introduce a metric, Semantic Relevance Gesture Recall (SRGR). Qualitative and quantitative experiments demonstrate metrics' validness, ground truth data quality, and baseline's state-of-the-art performance. To the best of our knowledge, BEAT is the largest motion capture dataset for investigating human gestures, which may contribute to a number of different research fields including controllable gesture synthesis, cross-modality analysis, emotional gesture recognition. The data, code and model will be released for research.

1 Introduction

Synthesizing conversational gestures can be helpful for animation, entertainment, education and virtual reality applications. To accomplish this, the complex relationship among speech, facial expressions, emotions, speaker identity and semantic meaning of gestures has to be carefully considered in the design of the gesture synthesis models.

While synthesizing conversational gestures based on audio [32,52,20] or text [53,8,5,3] has been widely studied, synthesizing realistic, vivid, human-like conversational gestures is still unsolved and challenging for several reasons. i) Quality and scale of the dataset. Previously proposed methods [52,32] were trained on limited mo-cap datasets [46,17] or on pseudo-label [20,52,21] datasets (See Tab. 1), which results in limited generalization capability and lack of robustness. ii) Rich and paired multi-modal data. Previous works adopted one or two modalities [20,53,52] to synthesize gestures and reported that conversational gestures are determined by multiple modalities together. However, due to the lack of paired multi-modal data, the analysis of other modalities, e.g., facial expression, for gesture synthesis is still missing. iii) Speaker style disentanglement. All available datasets, as shown in Tab. 1, either have only a single or two speakers[17], or many speakers but different speakers talk about different topics [21,52,20]. Speaker-specific styles were not much investigated in previous studies due to the lack of data. iv) Emotion annotation. Existing work[7] analyzes the emotion-conditioned gestures by extracting implicit sentiment features from the text. Due to the unlabeled, limited emotion categories in the dataset[52], it cannot cover enough emotion in daily conversations. v) **Semantic relevance**. Due to the lack of semantic relevance annotation, only a few works 31,52 analyze the correlation between generated gestures and semantics though listing subjective visualization examples. It will enable synthesizing context related meaningful gestures if exists semantic labels of gestures. As a conclusion, the absence of a large-scale, high-quality multi-modal dataset with semantic, emotional annotation is the main obstacle in achieving human-like conversational gestures synthesis.

There are two design choices for collecting unlabeled multi-modal data, i) the pseudo-label approach[20,52,21], i.e., extracting conversational gestures, facial landmarks from in-the-wild videos using 3d pose estimation algorithms[12] and ii) the motion capture approach[17], i.e., recording the data of speakers through predefined scenes or texts. In contrast to the pseudo-labeling approach, which allows for low-cost, semi-automated access to large-scale training data, e.g., 97h[52], motion-captured data requires a higher cost and more manual work resulting in smaller dataset sizes, e.g., 4h[17]. However, Due to the motion capture can be strictly controlled and designed in advance, it is able to ensure the quality and diversity of the data, e.g., eight different emotions of the same speaker, and different gestures of 30 speakers talking the same sentences. Besides, high-quality motion capture data are indispensable to evaluate the effectiveness of pseudo-label training.

Table 1. Comparison of Datasets. We compare with all 3D conversational gesture and face datasets. "#" indicates the number, best and second are highlighted. Our dataset is the largest mocap dataset with multi-modal data and annotations

	Quailty	Modality					Annotation		Scale		
dataset	GT?	#body	$\#\mathrm{hand}$	face	audio	text	$\#\mathrm{speaker}$	#emo	sem	#seq	dura
TED[52]	pseudo	9	-	-	En	√	N/A	-	-	1400	97h
S2G[20,21]	label	14	42	2D	En	-	6	-	-	N/A	33h
MPI[47]		23	-	-	-	√	1	11	-	1408	1.5h
VOCA[16]		-	-	3D	En	-	12	-	-	480	0.5h
Takechi[46]	mo-cap	24	38	-	$_{ m Jp}$	-	2	-	-	1049	5h
Trinity $[17]$		24	38	-	En	\checkmark	1	-	-	23	4h
Ours	mo-cap	27	48	3D	E/C/S/J	✓	30	8	✓	2508	76h

Based on the above analysis, to address these data-related problems, we built a mo-cap dataset BEAT containing semantic and eight different emotional annotations, from 30 speakers in four modalities of Body-Expression-Audio-Text, annotated by the average of 10 annotators in a total of 30M frames. The motion capture environment is strictly controlled to ensure quality and diversity, with a total of 76 hours and more than 2500 topic-segmented sequences. Speakers with different language mastery provided data in three other languages at different durations and in pairs. The ratio of different actors/actresses, range of phonemes, variety of languages is carefully designed to cover natural language characteristics. For emotional gestures, feedback on the speakers' expressions was provided by professional instructors during the recording process, and re-recorded in case of non-expressive gesturing to ensure the expressiveness and quality of the entire dataset. After statistical analysis on BEAT, we observed the correlation of conversational gestures with facial expressions, emotions, and semantics, in addition to the known correlation with audio, text, and speaker identity. Additionally, we propose a baseline neural network architecture, Cascaded Motion Network (CaMN), which learns synthesizing body and hand gestures by inputting all six modalities mentioned above. The proposed model consists of cascaded encoders and decoders for enhancing the contribution of audio and facial modalities.

In addition, in order to evaluate the diversity synthesized gestures, we propose Semantic-Relevant Gesture Recall (SRGR), which weights Probability of Correct Keypoint (PCK) based on semantic scores of the ground truth data. Overall, our contributions can be summarized as follows:

- We release BEAT, which is the first gesture dataset with semantic and emotional annotation, and the largest motion capture dataset in terms of duration and available modalities to the best of our knowledge.
- We propose CaMN as a baseline model that inputs audio, text, facial blendweight, speaker identity, emotion and semantic score to synthesize conversational body and hands gestures through cascaded network architecture.
- We introduce SRGR to evaluate the diversity of synthesized gestures as well as the human preference of conversational gestures.

Finally, qualitative and quantitative experiments demonstrate SRGR's validness, ground truth data quality, and baseline model's state-of-the-art performance.

2 Related Work

Conversational Gestures Dataset. We first review mo-cap and pseudo-label conversational gestures datasets. Volkova et al.[47] built a mo-cap emotional gestures dataset in 89 mins with text annotation, Takeuchi et al. [45] captured an interview-like audio-gesture dataset in total 3.5-hour with two Japanese speakers. Ferstl and Mcdonnell[17] collected a 4-hour dataset, Trinity, with a single male speaker though discussing hobbies, etc, which is the most commonly used mocap dataset for conversational gestures synthesis. On the other hand, Ginosar et al. [20] used OpenPose [12] to extract 2D poses from YouTube videos as training data for 144 hours, called S2G Dataset. Habibie et al.[21] extended it to a full 3D body with facial landmarks, and the last available data is 33 hours. Similarly, Yoon et al. [52] used VideoPose3D[39] to build on the TED dataset, which is 97 hours with 9 joints on the upper body. The limited data amount of mo-cap and noise in ground truth makes a trade-off for the trained networks generalization capability and quality. Similar to our work, several datasets are built for talkingface generation and the datasets can be divided into 3D scan face, e.g., VOCA[46] and MeshTalk[42] or RGB images[4,11,15,26,49]. However, these datasets cannot be adopted to synthesize human gestures.

Semantic or Emotion-Aware Motion Synthesis. Semantic analysis of motion has been studied in the action recognition and the sign-language analysis/synthesis research domains. For example, in some of action recognition datasets[25,28,13,14,43,9,34,44,40,48] clips of action with the corresponding label of a single action, e.g., running, walking[41] is used. Another example is audiodriven sign-language synthesis[27], where hand gestures have specific semantics. However, these datasets are not applicable to conversational gestures synthesis, since gestures used in natural conversations are more complex than single actions and their semantic meaning is different from sign-language semantics. Recently, Bhattacharya[7] extracted emotional cues from text and used them for gesture synthesis. However, the proposed method has limitations in the accuracy of the emotion classification algorithm and the diversity of emotion categories in the dataset.

Conditional Conversational Gestures Synthesis. Early baseline models were released with datasets such as text-conditioned gesture [53], audio-conditioned gesture [20,45,17], and audio-text-conditioned gesture [52]. These baseline models were based on CNN, LSTM for end-to-end modeling. Several efforts try to improve the performance of the baseline model by input/output representation selection [30,19], adversarial training [18] and various types of generative modeling techniques [50,36,51,1], which can be summarized by "Estimating a better distribution of gestures based on the given conditions.". As an example, StyleGestures [2] uses Flow-based model [23] and additional control signal to sample gesture from the distribution. Probabilistic gesture generation enables generating diverse gestures based on noise, and they are achieved by CGAN [51], WGAN [50]. However, due to the lack of paired multi-modal data, the analysis of other modalities, e.g., facial expression, for gesture synthesis is still missing.

3 BEAT: Body-Expression-Audio-Text Dataset

In this section, we introduce the proposed Body-Expression-Audio-Text (BEAT) Dataset. First, we describe the dataset acquisition process and then introduce the annotation of text, emotion, and semantic relevance information. Finally, we use BEAT to analyze the correlation between conversational gestures and emotions and show the distribution of semantic relevance.

3.1 Data Acquisition

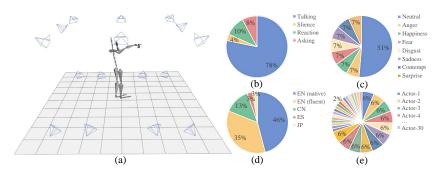


Fig. 2. Capture System and Subject Distribution of BEAT. (a) A 16-camera motion capture system is adopted to record data in Conversation and Self-Talk sessions. (b) Gestures are divided into four categories in Conversation session. (c) Seven additional emotion categories are set in equal proportions in the self-talk session. Besides, (d) our dataset includes four languages which mainly consist of English, (e) by 30 speakers from ten countries with different recording duration.

Motion Capture System. The motion capture system shown in Fig. 2a, is based on 16 synchronized cameras recording motion in 120 Hz. We use Vicon's suits with 77 markers (refer to supp. for the location of markers on the body). The facial capture system is using ARKit with depth camera on iPhone 12 Pro, which extracts 52 blendshape weights in 60 Hz. The blendshape targets are designed based on Facial Action Coding System (FACS), and are widely used from novice users to industries. The audio is recorded in a 48kHz stereo.

Design Criteria. BEAT is equally divided into *conversation* and *self-talk* sessions, which consist of 1-min and 10-min sequences, respectively. The conversation is between the speaker and the instructor remotely, i.e., to ensure only the speaker's voice is recorded. As shown in Fig. 2b, The speaker's gestures are divided into four categories as talking, instantaneous reactions to questions, the state of thinking (silence) and asking. We timed each category's duration during the recording process. Topics were selected from 20 predefined topics, which cover 33% and 67% debate and description topics, respectively. *Conversation* sessions would record the neutral conversations as well as ensure the diversity of the dataset. The *self-talk* sessions consist of 120 1-minute self-talk recordings,

where speakers answer questions about daily conversation topics, e.g., personal experiences or hobbies. The answers were written and proofread by three English native speakers, and the phonetic coverage was controlled to be similar to the frequently used 3000 words[24]. We covered 8 emotions, neutral, anger, happiness, fear, disgust, sadness, contempt and surprise, in the dataset referring to [35] and the ratio of each emotion is shown in Fig. 2c. Among the 120 questions, 64 of them were for neutral emotions and the remaining seven emotions had eight questions each. Different speakers were asked to talk about the same content with their personalized gestures. Details about predefined answers, pronunciation distribution are available in the supplementary materials.

Speaker Selection and Language Ratio. We strictly control the proportion of languages as well as accents to ensure the generalization capability of the dataset. As shown in Fig. 2d, the dataset consists mainly of English data: 60h (81%), and 12h of Chinese, 2h of Spanish and Japanese. The Spanish and Japanese are also 50% of the size of the previous mo-cap dataset[17]. The English component includes 34h of 10 native English speakers, including the US, UK, and Australia, and 26h of 20 fluent English speakers from seven other countries. As shown in Fig. 2e, 30 speakers (including 15 females) from different ethnicities can be grouped into two depending on their total recording duration as 4-hour (10 speakers) and 1-hour (20 speakers), where the 1-hour data is proposed for few-shot learning experiments. It is recommended to check the supplementary material for details of the speakers.

Recording. Speakers were asked to read answers in self-talk sections proficiently. However, they were not guided to perform a specific style of gesture, but were encouraged to show a natural, personal, daily style of conversational gestures. Speakers would watch 2-10 minutes of emotionally stimulating videos corresponding to different emotions before talking with the particular emotion, and they would be instructed by a professional speaker to elicit the corresponding emotion correctly. We re-record any unqualified data to ensure the data correctness and quality. During the conversation, the instructor will guide the speaker to describe the experience of different emotions.

3.2 Data Annotation

Text Alignment. We use an in-house built Automatic Speech Recognizer (ASR) to obtain the initial text for the conversation session and proofread by annotators. Then, we adopt Montreal Forced Aligner (MFA) aligner[37] for temporal alignment of the text with audio.

Emotion and Semantic Relevance. The 8-class emotion label of self-talk is already confirmed and the correctness is already guaranteed by the on-site supervision. For the conversation session, annotators would watch the video with corresponding audio and gestures to perform frame-level annotation. For the semantic relevance, we average the binary score of 10 annotators as the final semantic score since the semantic is subjective. We assigned 600 annotators from Amazon Mechanical Turk (AMT). The annotators were asked to annotate

a small amount of test data as a qualification check, of which only 118 annotators were succeeded in the qualification phase for the final data annotation. In this task, we paid \sim \$12 for each annotator per hour. The data was set to 10 times in advance and the same annotators could not annotate the same data twice.

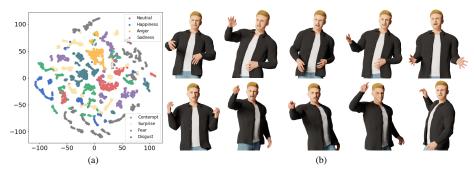


Fig. 3. Emotional Gesture Clustering and Examples. (a) T-SNE visualization for gestures in eight emotion categories. Gestures with different emotions are basically distinguished into different groups, e.g., the Happiness (blue) and Anger (orange). (b) Examples of Happiness (top) and Anger gestures from speaker-2.

3.3 Data Analysis

The collection and annotation of BEAT have made it possible to analyze correlations between conversational gestures and other modalities. While the connection between gestures and audio, text and speaker identity has been widely studied. We further discuss the correlations between gestures and facial expressions, emotions and semantics.

Facial Expression and Emotion. Facial expressions and emotions were strongly correlated (excluding some of the lip movements), and analysis of the correlation between conversational gestures and emotional categories allowed the correlation of gestures with emotion labels and facial expressions to be verified simultaneously. As shown in Fig. 3a, We visualized the gestures in T-SNE based on a 2s-rotation representation, and the results showed gestures have different characteristics in different emotions. For example, as shown in Fig. 3b, speaker 2 has different gesture styles when angry and happy, e.g., the gestures are larger and faster when angry. The T-SNE results also show a significant difference between happy (blue) and angry (yellow). However, the gestures for the different emotions are still not perfectly separable by the rotation representation. Furthermore, the gestures of the different emotions appear to be confounded in each region, which is also consistent with subjective perceptions. Overall, conversational gestures are found to be related to emotions and facial expressions.

Distribution of Semantic Relevance. There is large randomness for the semantic relevance between gestures and texts, which is shown in Fig. 4, where the frequency, position and content of the semantic-related gestures vary from

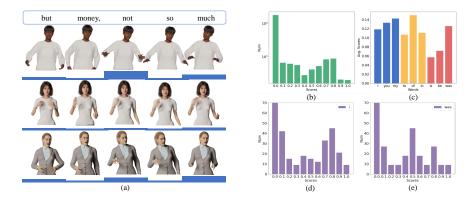


Fig. 4. Distribution of Semantic Annotation. (a) Different speaker ID speaks in a same phase happens different levels of semantic relevance and different styles of gesture. (b) The overall semantic distribution of BEAT. (c) The semantic relevance of the high frequency words which are grouped by their lexical in different color. (d,e) Different distribution of semantic relevance happens in words i and was even sharing almost the same level of semantic relevance.

speaker to speaker when the same text content is uttered. In order to better understand the distribution of the semantic relevance of the gestures, we conducted a semantic relevance study based on 4 hours of two speakers' data. As shown in Fig. 4 (b), for the overall data, 83% of the gestures are with low semantic scores (≤ 0.2). For the words-level, the semantic distribution varied between words, e.g., i and was which are sharing a similar semantic score but are different in the score distribution. Besides, Fig. 4 (c) shows the average semantic scores of 9 high-frequency words in the text corpus. It is to be mentioned that the scores of the Be-verbs showed are comparatively lower than those Pronouns and Prepositions which are shown in blue and yellow respectively. Ultimately, it presents a different probability distribution to the semantically related gestures respectively.

4 Multi-Modal Conditioned Gestures Synthesis Baseline

In this section, we propose a baseline that inputs all the modalities for generating vivid, human-like conversational gestures. The proposed baseline, Cascaded Motion Network (CaMN), is shown in Fig. 5, which encodes text, emotion condition, speaker identity, audio and facial blendshape weights to synthesize body and hands gestures in a multi-stage, cascade structure. The semantic relevance is adopted as loss weights to make the network generate more semantic relevance gestures. The text, audio and speaker ID encoders network selection are referred to [52] and customized for better performance. All input data have the same time resolution as the output gestures so that the synthesized gestures can be processed frame by frame through a sequential model. The gesture and facial blendshape weights are downsampled to 30 FPS, and the word sentence is inserted padding tokens to correspond to the silence time in the audio.

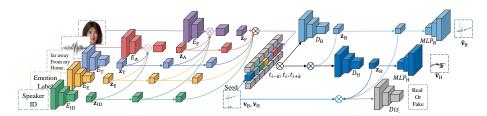


Fig. 5. Cascaded Motion Network (CaMN). As a multi-modal gesture synthesis baseline, CaMN inputs text, emotion label, speaker ID, audio and facial blendweight in a cascaded architecture, the audio and facial feature will be extracted by concatenating the features of previous modalities. The fused feature will be reconstructed to body and hands gestures by two cascaded LSTM+MLP decoders.

Text Encoder. First, words are converted to word embedding set $\mathbf{v}^{\mathrm{T}} \in \mathbb{R}^{300}$ by pre-trained model in FastText[10] to reduce dimensions. Then, the word sets are fine-tuned by customized encoder E_{T} , which is a 8-layer temporal convolution network (TCN)[6] with skip connections[22], as

$$z_i^{\mathrm{T}} = E_{\mathrm{T}}(v_{i-f}^{\mathrm{T}}, ..., v_{i+f}^{\mathrm{T}}), \tag{1}$$

For each frame i, the TCN fusions the information from 2f = 64 frames to generate final latent feature of text, the set of features is note as $\mathbf{z}^{\mathrm{T}} \in \mathbb{R}^{128}$.

Speaker ID and Emotion Encoders. The initial representation of speaker ID and emotion are both one-hot vectors, as $\mathbf{v}^{\mathrm{ID}} \in \mathbb{R}^{30}$ and $\mathbf{v}^{\mathrm{E}} \in \mathbb{R}^{8}$. Follow the suggestion in [52], we use embedding-layer as speaker ID encoder, E_{ID} . As the speaker ID does not change instantly, we only use the current frame speaker ID to calculate its latent features. on the other hands, we use a combination of 4-layer TCN and embedding-layer as the emotion encoder, E_{E} , to extract the temporal emotion variations.

$$z_i^{\rm ID} = E_{\rm ID}(v_i^{\rm ID}), z_i^{\rm E} = E_{\rm E}(v_{i-f}^{\rm E}, ..., v_{i+f}^{\rm E}), \tag{2}$$

where $\mathbf{z}^{\text{ID}} \in \mathbb{R}^8$ and $\mathbf{z}^{\text{E}} \in \mathbb{R}^8$ is the latent feature for speaker ID and emotion, respectively.

Audio Encoder. We adopt the raw wave representation of audio and downsample it to 24kHZ, considering audio as 30FPS, for each frame we have $\mathbf{v}^{A} \in \mathbb{R}^{8000}$. We feed the audio joint with the text, speakerID and emotion features into audio encoder E_{A} to learn better audio features. As

$$z_i^{\mathcal{A}} = E_{\mathcal{A}}(v_{i-f}^{\mathcal{A}}, ..., v_{i+f}^{\mathcal{E}}; v_i^{\mathcal{T}}; v_i^{\mathcal{E}}; v_i^{\mathcal{ID}}),$$
(3)

The $E_{\rm A}$ consists of 12-layer TCN with skip connection and 2-layer MLP, the features in other modifies are concatenated with the 12th layer audio features, thus the final MLP layers are for audio feature refinement and the final latent audio feature is $\mathbf{z}^{\rm A} \in \mathbb{R}^{128}$.

Facial Expression Encoder. We take the $\mathbf{v}^F \in \mathbb{R}^{52}$ as initial representation of facial expression. 8-layer TCN and 2-layer MLP based encoder E_F is adopt to extract facial latent feature $\mathbf{z}^F \in \mathbb{R}^{32}$, as

$$z_i^{F} = E_F(v_{i-f}^{F}, ..., v_{i+f}^{F}; v_i^{T}; v_i^{E}; v_i^{ID}; v_i^{A}), \tag{4}$$

the features are concatenated at 8th layer and the MLP is for refinement.

Body and Hands Decoders. We implement the body and hands decoders in separated, cascaded structure. which is based on [38]'s conclusion that the body gestures can be used to estimate hand gestures, these two decoders, $D_{\rm B}$ and $D_{\rm F}$ are based on the LSTM structure for latent feature extraction and 2-layer MLP for gesture reconstruction. They would combine the features of five modalities with previous gestures, i.e. seed pose, to synthesis latent gesture features $\mathbf{z}^{\rm B} \in \mathbb{R}^{256}$ and $\mathbf{z}^{\rm H} \in \mathbb{R}^{256}$. The final estimated body $\hat{\mathbf{v}}^{\rm B} \in \mathbb{R}^{27\times3}$ and hands $\hat{\mathbf{v}}^{\rm H} \in \mathbb{R}^{48\times3}$ are calculated as,

$$z_i^{\mathbf{M}} = z_i^{\mathbf{T}} \otimes z_i^{\mathbf{ID}} \otimes z_i^{\mathbf{E}} \otimes z_i^{\mathbf{A}} \otimes z_i^{\mathbf{F}} \otimes v_i^{\mathbf{B}} \otimes v_i^{\mathbf{H}}, \tag{5}$$

$$\mathbf{z}^{\mathbf{B}} = D_{\mathbf{B}}(z_0^{\mathbf{M}}, ..., z_n^{\mathbf{M}}), \mathbf{z}^{\mathbf{H}} = D_{\mathbf{H}}(z_0^{\mathbf{M}}, ..., z_n^{\mathbf{M}}; \mathbf{z}^{\mathbf{B}}), \tag{6}$$

$$\hat{\mathbf{v}}^{\mathrm{B}} = MLP_{\mathrm{B}}(\mathbf{z}^{\mathrm{B}}), \hat{\mathbf{v}}^{\mathrm{H}} = MLP_{\mathrm{H}}(\mathbf{z}^{\mathrm{H}}), \tag{7}$$

 $\mathbf{z}^{\mathrm{M}} \in \mathbb{R}^{549}$ is the merged features for all modalities. For Eq. 5, the length for seed pose is 8 frames.

Loss Functions. The final supervision of our network is based on the gesture reconstruction and the adversarial loss

$$\mathcal{L}_{Gesture Rec.} = \mathbb{E}\left[\left\| \mathbf{v}^B - \hat{\mathbf{v}}^B \right\|_{1} \right] + \alpha \mathbb{E}\left[\left\| \mathbf{v}^H - \hat{\mathbf{v}}^H \right\|_{1} \right], \tag{8}$$

$$\mathcal{L}_{\text{Adv.}} = -\mathbb{E}[\log(Dis(\hat{\mathbf{v}}^B; \hat{\mathbf{v}}^H))], \tag{9}$$

where the discriminator input to the adversarial training is only the gesture itself. We also adopt a weight α to balance the body and hands penalties. After that, during training, we adjust the weights of L1 loss and adversarial loss using the semantic-relevancy label λ The final loss function is

$$\mathcal{L} = \lambda \beta_0 \mathcal{L}_{Gesture Rec.} + \beta_1 \mathcal{L}_{Adv}, \tag{10}$$

where β_0 and β_1 are predefined weight for L1 and adversarial loss. When semantic-relevancy is high, we encourage the network to generate gestures that are spatially similar to ground truth as much as possible, thus strengthening the L1 penalty and decreasing the adversarial penalty. We empirically set 0.02, 100, 20 for α , β_0 and β_1 , respectively.

5 Metric for Gesture Diversity

We propose the Semantic-Relevant Gesture Recall (SRGR) to evaluate the diversity of gesture, which can also be interpreted as whether the gestures are vivid and diverse. We utilize the semantic scores as a weight for Probability of Correct Keypoint (PCK) between the generated gestures and the ground truth gestures. Where PCK is the number of joints that been successfully recalled against a specified threshold δ . The SRGR metric can be calculated as follows:

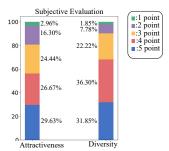
$$D_{SRGR} = \lambda \sum_{T \in \mathcal{T}} \frac{1}{T \times J} \sum_{t=1}^{T} \sum_{j=1}^{J} \mathbf{1} \left[\left\| p_t^j - \hat{p}_t^j \right\|_2 < \delta \right], \tag{11}$$

where $\mathbf{1}$ is the indicator function and T, J is the set of frames and number of joints. We think the SRGR, which emphasizes recalling gestures in the clip of interest is more in line with the subjective human perception for gesture diversity than the variance of synthesized gestures.

6 Experiments

In this section, we first evaluate the validity of the SRGR metric, and then we demonstrate the data quality of our dataset based on subjective experiments. Next, we demonstrate the validity of our baseline model using subjective and objective experiments, and finally, we discuss the contribution of each modality based on ablation experiments.

6.1 Validness of SRGR



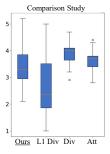


Fig. 6. User Study Results for SRGR. (left) The proportional histogram shows the distribution of the score of 5-point Likert scale. (Right) The scores of comparison study illustrate that SRGR is more akin to subjective human perception when evaluating a gesture. Div. and Att. indicates Diversity and Attractiveness, respectively.

A user study is conducted to evaluate the validness of SRGR. Firstly, we randomly trim the motion sequences with rendered results into clips that are around the 40s. For each clip, the participants are asked to evaluate the gesture based on its diversity which is the number of non-repeated gestures. Besides, the participants then need to score its attractiveness which should be based on

the motion itself instead of the content of the speech. Totally 160 participants took part in the evaluation study, each of them evaluates 15 random clips of gestures. Both of the questions follow a 5-points Likert scale which allows us to calculate the users' subjective score of the gesture diversity and attractiveness respectively. The experimental results are shown in Fig. 6 (left), which implies that there is a strong correlation between the attractiveness of a gesture and its diversity. More importantly, Fig. 6 (right) shows that SRGR is closer to the human perception in evaluating the diversity of gesture than the equal weight sum of L1 distance.

6.2 Data Quality

To evaluate the captured ground truth motion data quality, we compare our proposed dataset with the widely used mo-cap dataset Trinity[17]. We conduct the user study based on the comparison of clips sampled from ground truth, and generated results by motion synthesis networks trained in each dataset. For Trinity dataset, it has a total of 23 sequences, with 10 minutes each. We randomly divide the data into 19:2:2 for train/valid/test since there is no standard for splitting. Then, for S2G-3D dataset, we follow the splitting method introduced in their paper[21]. For our dataset, we used only the English part for training, and divided the data randomly into 50:5:5.

Table 2. User Study on Data Quality. BEAT get higher user preference score than Trinity[17] in the terms of ground truth data quality.

Training	Body Correctness			Hands Correctness			Diversity		Synchrony			
Dataset	S2G[20]	A2G[32]	GT	S2G	A2G	GT	S2G	A2G	GT	S2G	A2G	GT
Trinity	38.8	37.0	43.8	15.3	14.6	11.7	42.1	36.7	40.2	40.9	36.3	46.4
Ours	61.2	63.0	56.2	84.7	85.4	88.3	57.9	63.3	59.8	59.1	63.7	53.6

We used S2G[20], as well as the SoTA algorithm audio2gestures[32], to cover both GAN and VAE models. The output layer of the S2G model was adapted for outputting 3D coordinates (see supplementary material for details of the model training). In the ablation study, the final generated 3D skeleton results were rendered and composited with audio for comparing in the user study. A total of 120 participant subjects compared the clips which were randomly sampled from Trinity and our dataset, with 5-20s in length. The participants were asked to evaluate the gestures correctness, i.e., physical correctness, diversity and gesture-audio synchrony. And for the gesture correctness test, the body and hands were evaluated separately. The results are shown in 2, which demonstrates that our dataset received higher user preference in all aspects. Especially for the hand movements, we outperformed the Trinity dataset by a large margin. This is probably due to the noise of the past motion capture devices and the lack of markers on the hands.

Table 3. Evaluation on BEAT. Our Table 4. Results of Ablation Study. CaMN performs best in the term of FGD, SRGR and BeatAlign, all methods are trained on our dataset (BEAT)

	FGD	SRGR ↑	BeatAlign ↑
Seq2Seq[53]	261.3	0.173	0.689
S2G[20]	256.7	0.092	0.712
A2G[32]	223.8	0.097	0.724
MultiContext[52]	176.2	0.196	0.749
CaMN (Ours)	123.7	0.239	0.783

	FGD ↓	BGSR ↑	BeatAlign ↑
full cascated	123.7	0.239	0.783
w/o cascaded	137.2	0.207	0.776
w/o text	149.4	0.171	0.781
w/o audio	155.7	0.225	0.729
w/o speaker ID	159.1	0.207	0.774
w/o face	163.3	0.217	0.736
w/o emotion	151.7	0.231	0.775
w/o semantic	151.8	0.194	0.786

Evaluation of the baseline model

Training Setting. We use the Adam optimizer [29] to train at a learning rate of 2e-4, and the entire dataset is trained for 15 hours in a 1*V100 environment. For evaluation metrics, L1 has been demonstrated not suitable to evaluate the gesture performance [32,52], thus we adopt FGD [52] to evaluate whether the generated gestures' distribution distance with ground truth. It computes the distance between latent features extracted by a pretrained network, we use an LSTM-based autoencoder as the pretrained network. In addition, we adopt SRGR and BeatAlign as the evaluation of diversity and synchrony. BeatAlign[33] is a Chamfer Distance between audio and gesture beats to evaluate gesture-audio beat similarity.

Quantitative Results. The final results are shown in Tab. 3. In addition to S2G and A2G, we also compare our results with text-to-gesture and audio&testto-gesture algorithm, Seq2Seq[53] and MultiContext[52]. The results show that both of our end2end model and cascaded model archive SoTA performance in all metrics. The visualization result of our model is shown in Fig. 7a, which shows CaMN can generate semantic relevant gestures.

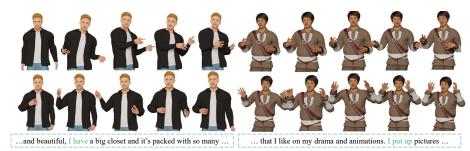


Fig. 7. Results Visualization. Left: ground truth (top) and generated results. Right: emotion style transfer result from neutral (top) to fear.

6.4 Ablation Study.

We conducted an ablation study to discuss the effectiveness of cascaded connection and each modality. For cascaded connection, in contrast to the end-to-end approach, our method is able to achieve better performance because we introduce prior human knowledge to help the network extract features of different modalities. For multi-modal data, we gradually removed the data of one modality during the experiment. The complete experimental results are shown in Tab. 4.

Synchrony would significantly be reduced after removing the audio, which is intuitive. However, it still maintains some of the synchronizations as the padding and time-align annotation of the text and the lip motion of the facial expression, which is demonstrated by removing the facial and text data. In contrast, eliminating semantic weighted loss improves synchrony, which means that semantic gestures are usually not strongly aligned with audio perfectly. There is also a relationship between emotion and synchrony, but speaker ID only has little effect on synchrony. The removal of audio, emotion, and facial expression, does not have a significant effect on the semantic relevant gesture recall, which depends mainly on the text and the speaker ID.

Data from each modality contributed to improving the FGD, which means using different modalities data enhances the network's mapping ability. The unities of audio and facial expressions, especially facial expressions, improve the FGD significantly. We found that removing emotion and speaker ID also impacts the FGD scores. This is because the use of the integrated network increases the diversity of features, which leads to a diversity of results, increasing the variance of the distribution, making it more like the original data.

6.5 Controllability

We can achieve emotion transfer for the same sentence by changing the input of emotion label and facial expressions, and we show a series of subjective results in Fig. 7 (right) for demonstration. As shown in the figure, when the gesture is transferred from natural to fear, it presents different style of the gestures, e.g., the hands are moving around the head.

7 Limitation and Conclusions

There is room for improvement in this present research, SRGR now is calculated based on semantic annotation, which has a limitation for un-labeled dataset. To solve this problem, training a scoring network or semantic discriminator are possible direction.

As a conclusion, in this paper we build a large-scale, high-quality, multi-modal, semantic and emotional annotated dataset to generate more human-like, semantic and emotional relevant conversational gestures. Together with the dataset, we propose a cascade-based baseline model for gesture synthesis based on six modalities and archieve SoTA performance, Finally we introduce SRGR for evaluating the diversity of gesture as well as user preference. Our dataset and the related statistical experiments could benefit a number of different research fields including controllable gesture synthesis, cross-modality analysis and emotional motion recognition in the future.

8 Acknowledgements

This work was conducted during Haiyang Liu, Zihao Zhu, Yichen Peng's internship at Tokyo Research Center. We thank Hailing Pi for communicating with the recording actors of the BEAT dataset.

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