

Speech2Properties2Gestures: Gesture-Property Prediction as a Tool for Generating Representational Gestures from Speech

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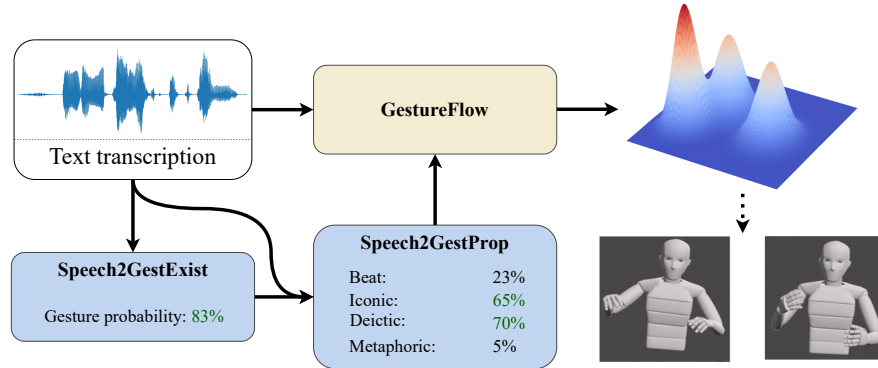


Figure 1: Overview of the proposed framework. We first use speech text and audio to predict whether or not the agent should gesture. After that, we predict several gesture properties, such as gesture type. Finally, gestures are generated by a probabilistic model (e.g., a normalizing flow) conditioned on text, audio, and predicted gesture properties together.

ABSTRACT

We propose a new framework for gesture generation, aiming to allow data-driven approaches to produce more semantically rich gestures. Our approach first predicts whether to gesture, followed by a prediction of the gesture properties. Those properties are then used as conditioning for a modern probabilistic gesture-generation model capable of high-quality output. This empowers the approach to generate gestures that are both diverse and representational. Follow-ups and more information can be found on the project page: <https://svito-zar.github.io/speech2properties2gestures/>

CCS CONCEPTS

• **Human-centered computing** → *Human computer interaction (HCI)*; • **Computing methodologies** → **Animation**.

KEYWORDS

gesture generation, virtual agents, representational gestures

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1 INTRODUCTION AND BACKGROUND

A large part of human communication is non-verbal [10] and often takes place through co-speech gestures [9, 19]. Co-speech gesture behavior in embodied agents has been shown to help with learning tasks [5] and lead to greater emotional response [24]. Gesture generation is hence an important part of both automated character animation and human-agent interaction.

Early dominance of rule-based approaches [6, 12, 18, 21] has been challenged by data-driven gesture generation systems [1, 4, 7, 14, 20, 26, 27]. These latter systems first only considered a single speech modality (either audio or text) [4, 13, 20, 27], but are now shifting to use both audio and text together [1, 14, 26].

While rule-based systems provide control over the communicative function of output gestures, they lack variability and require much manual effort to design. Data-driven systems, on the other hand, need less manual work and are very flexible, but most existing systems do not provide much control over communicative function and generated gestures have little relation to speech content [15].

This paper continues recent efforts to bridge the gap between the two paradigms [7, 23, 29]. The most similar prior work is Yunus et al. [29] where gesture timing and duration were predicted based

Label	Gesture category [Macro F ₁]				Gesture semantics [Macro F ₁]				Gesture phase [F ₁]				
	deictic	beat	iconic	discourse	amount	shape	direction	size	pre-hold	post-hold	stroke	retr.	prep.
Relative frequency	29.05%	14.47%	72.03%	12.78%	4.7%	13.1%	13.7%	1.9%	0.6%	12.2%	40.9%	14.8%	30.8%
RandomGuess	50% ± 2%	50% ± 2%	50% ± 1.5%	50% ± 2%	49% ± 1%	49% ± 2%	49% ± 2%	50% ± 1%	1.3% ± 4%	12% ± 4%	42% ± 4%	14% ± 5%	30% ± 3%
ProposedModel	60% ± 6%	53% ± 6%	63% ± 5%	59% ± 7%	63% ± 8%	65% ± 6%	62% ± 8%	59% ± 9%	0.5% ± 1.3%	23% ± 12%	47% ± 10%	25% ± 5%	45% ± 6%

Table 1: Gesture-property prediction scores for random guessing and our trained predictors using text and audio modalities together. Bold, coloured numbers indicate that the label in question can be predicted better than chance.

on acoustic features only. The method proposed here differs from their approach in three ways: 1) it considers not only audio but also text as input; 2) it models not only gesture phase, but multiple gesture properties; 3) it also provides a framework for integrating these gesture properties in a data-driven gesture-generation system.

The proposed approach helps decouple different aspects of gesticulation and can leverage database information about gesture timing and content with modern, high-quality data-driven animation.

2 PROPOSED MODEL

Our unified model uses speech text and audio as input to generate gestures as a sequence of 3D poses. As depicted in Figure 1, it is composed of three neural networks:

- (1) **Speech2GestExist**: A temporal CNN which takes speech as input and returns a binary flag indicating if the agent should gesture (similar to [28]);
- (2) **Speech2GestProp**: A temporal CNN which takes speech as input and predicts a set of binary gesture properties, such as gesture type, gesture phase, etc.;
- (3) **GestureFlow**: A normalizing flow [11] that takes both speech and predicted gesture properties as input, and describes a probability distribution over 3D poses, from which motion sequences can be sampled.

In this study, we experiment with the first two neural networks only. We implemented the *Speech2GestProp* and *Speech2GestExist* components using dilated CNNs. Their inputs are sequences of aligned speech text and audio frames, and they return a binary vector of gesture properties (for *Speech2Prop*) or a binary flag of gesture existence (for *Speech2GestExist*) as its output. By sliding a window over the speech and predicting poses, frame-by-frame properties are generated at 5 fps. Text features were extracted using DistilBERT [22]. Audio features were log-scaled mel-spectrograms.

3 PRELIMINARY RESULTS

Dataset. We evaluated our model on the SaGA direction-giving dataset [17] designed to contain many representational gestures. The dataset contains audio/video recordings of 25 participants (all German native speakers) describing the same route to other participants and includes detailed annotations of gesture properties.

We considered the following three gesture properties: 1) *Phase* (preparation, pre-stroke hold, stroke, post-stroke hold, and retraction); 2) *Type* (deictic, beat, iconic [19], and discourse); 3) *Semantic information* (amount, shape, direction, size, as described in [3]).

Experimental Results. For each of our experiments we calculated the mean and standard deviation of the F₁ score across 20-fold cross-validation. The F₁ score is preferable over accuracy here since the data is highly unbalanced and accuracy does not represent overall

performance well. For gesture category and phase we report Macro F₁ score [25], since those properties are not mutually exclusive.

First we validated that gesture presence can be predicted from the speech in our dataset. We achieved a $70\% \pm 3.7\%$ Macro F₁ score for binary classification, which aligns with previous work [28].

Next, we experimented with predicting gesture properties. Table 1 contains results for predicting the gesture category, gesture semantic information, and gesture phase from speech text and audio. We can see that this is a challenging task, but we are still able to predict most of the values better than chance. This was unexpected given how complex gesture semantics tend to be and could be due to the focused scope of the direction-giving task. For a deeper study with more results and analyses, please see the follow-up work [16].

4 DISCUSSION

In this section we discuss the feasibility of the proposed approach. Our proposal to use probabilistic models (especially normalizing flows) is inspired by a recent application of MoGlow [8] to perform gesture synthesis by Alexanderson et al. [2]. They showed that such models can be seamlessly conditioned on various kinematic gesture properties (such as speed, range, and hand height), suggesting that it is possible to condition gestures on semantic properties as well.

We obtained good results for the gesture-property prediction part of our proposed system, as described in Section 3. Since we can predict several important properties with F₁ scores significantly above chance level, we believe that our predictions are reasonable and will be useful for more appropriate gesture synthesis.

Our two-stage approach lets the machine learning model leverage additional information (such as detailed annotation) about human gestures. It also allows direct control of gesture frequency, by adjusting the threshold on the output of *Speech2GestExist* needed to trigger a gesture. Finally, it helps the model learn from small datasets, since each sub-module has a more straightforward task than learning everything at once and also can be trained separately.

5 CONCLUSION

We presented a novel gesture generation framework aiming to bridge the semantic gap between rule-based and data-driven models. Our method first predicts if a gesture is appropriate for a given point in the speech and what kind of gesture is appropriate. Once this prediction is made, it is used to condition the gesture generation model. Our gesture-property prediction results are promising and indicate that the proposed approach is feasible.

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