Let’s face it: Probabilistic multi-modal interlocutor-aware generation of facial gestures in dyadic settings

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ABSTRACT
To enable more natural face-to-face interactions, conversational agents need to adapt their behavior to their interlocutors. One key aspect of this is generation of appropriate non-verbal behavior for the agent, for example facial gestures, here defined as facial expressions and head movements. Most existing gesture-generating systems do not utilize multi-modal cues from the interlocutor when synthesizing non-verbal behavior. Those that do, typically use deterministic methods that risk producing repetitive and non-vivid motions. In this paper, we introduce a probabilistic method to synthesize interlocutor-aware facial gestures – represented by highly expressive FLAME parameters – in dyadic conversations. Our contributions are: a) a method for feature extraction from multi-party video and speech recordings, resulting in a representation that allows for independent control and manipulation of expression and speech articulation in a 3D avatar; b) an extension to MoGlow, a recent motion-synthesis method based on normalizing flows, to also take multi-modal signals from the interlocutor as input and subsequently output interlocutor-aware facial gestures; and c) subjective and objective experiments assessing the use and relative importance of the different modalities in the synthesized output. The results show that the model successfully leverages the input from the interlocutor to generate more appropriate behavior.

1 INTRODUCTION
Generating appropriate facial gestures (here defined as facial expressions and head movements) for a conversational agent in a dyadic setting is a task as intriguing as it is challenging. Its usefulness in human-agent interaction has been researched extensively [4, 43, 47] and there have been many attempts at realizing its potential in both virtual agents [38, 54] and social robots [58]. Interpersonal dynamics in face-to-face conversation includes many phenomena that affect the interaction in different ways, such as mimicry – the tendency to adopt poses, facial expressions, mannerisms, and speaking styles of the interlocutor. For example, it has been shown that when a conversational agent just copies the facial expressions of the human interlocutor with some delay it is perceived as more trustworthy [4]. Furthermore, Cassell and Thorsinson [10] found that so-called envelope feedback (e.g. gaze, manual beat gestures, and head movements) to be more important for the user than emotional feedback when interacting with conversational agents. Although there are many systems which use multi-modal input from the interlocutor, most of these systems often adapt and change only the semantic output of the system rather than the non-verbal output; some examples are [39, 52]. For non-verbal behavior generation it is typical to only use speech and/or semantic content produced by the agent as inputs to the system [30, 32, 38, 58]. MoGlow [3] is an example of a system which produces (full body) gestures in a probabilistic fashion, leading to non-repetitive, natural looking motion, but unaware of any interlocutor. Recently a few systems have been introduced that use either facial or facial and auditory input from the interlocutor [1, 19, 23, 29] to control non-verbal output from the system. We continue this line of work and present a probabilistic system, based on normalizing flows, for generating facial gestures in dyadic settings. Our system takes in audio from both conversational partners and facial gestures of the interlocutor and generates corresponding appropriate facial gestures for the virtual agent in a given context. A few randomly selected examples generated using our method can be found here: vimeo.com/showcase/7219185. We evaluate this system using segments annotated as containing mimicry from a database of dyadic interactions, as salient examples of interlocutor-dependent non-verbal behavior. Our stimulus-generation method allowed manipulating speech articulation independently from the facial gestures, allowing for varying the facial gestures while controlling for the effect of speech context. We find that:

• Participants can distinguish mimicry segments from mismatched segments (from the same interaction but another point in time) and find mimicry segments more appropriate. This also validates that our feature extraction and stimulus generation method appropriately captures non-verbal behavior.
• Feeding our model mismatched input segments yields a less appropriate response to the interlocutor, showing that our model leverages the multi-modal signals from the interlocutor to generate more appropriate facial gestures.
• While removing the facial gesture input from the interlocutor led to less appropriate behavior, the interlocutor’s audio was not beneficial for facial-gesture generation in our scenario.

2 RELATED WORK

2.1 Representing facial communicative signals

When using multi-modal signals in machine learning, it is of importance to choose appropriate parameterization methods. Our scenario and experiments impose the following requirements: To begin with, we require a parameterization that allows us to encode facial gestures from video (to be used as inputs and output to the models) in a person-independent way. Secondly, we need to be able to generate an animated 3D avatar, which means that there must exist a reliable inversion of the parameterization such that a signal rendering that expresses the perceptually relevant elements can be obtained. Thirdly, we need independent control over speech articulation and facial expression, in order to be able to run experiments with out-of-context gestures, where we replace the non-verbal behavior but retain the articulation; see Section 5. Finally, there must be a fully automatic process for analyzing video and synthesizing 3D avatars that allows unsupervised processing of several hours of video from different talkers.

We now discuss several existing face parameterization schemes and how they fit our requirements. Ekman & Friesen’s Facial Action Coding System (FACS) [17] was developed for subject-independent coding of facial expressions for psychology research. It has been widely used also in graphics and machine-learning applications [12, 15, 21, 28], but while FACS is well suited for coding, e.g., emotional expressions, it is less ideal for speech animation. There is also no canonical way of automatically encoding and decoding between video and FACS.

Another commonly used parametrization is facial landmarks, for example the 68 point Multi-PIE scheme, e.g., used in [19]. Facial landmarks often lack resolution and are not fully able to represent facial expressions and emotions [41]. They also lead to subject-specific data and cannot easily be used in generation. MPEG-4 Face Animation Parameters (FAP) are closely related to FACS but were designed to cope with both analysis and synthesis and are, for example, used as output parameters in [15]. There is however a lack of reliable tools for re-construction/synthesis. Statistically-based 3D analysis/synthesis parameterizations such as 3D morphable models [8] and Active Appearance Models [13] can yield high-quality results, but they typically rely on manual initialization steps that make them expensive to deploy in large-scale multi-talker machine learning settings with many hours worth of data.

FLAME [40] is a new parameterization that is able to represent facial expressions, shapes, and head rotation in a low-dimensional PCA parameter space that can be realized as a 3D mesh. The expression parameters can be automatically extracted from video. Our system uses the FLAME parameters as it improves the fidelity of facial gestures. FLAME allows for independent control over expression and shape by design. Using techniques described in Section 4.2 it is furthermore possible to independently drive speech articulation and facial expression.

2.2 Gesture generation

Several previous works have demonstrated successful generation of gestures of various kinds. Recent work in speech-driven hand-gesture generation, for example, has primarily been based on deep learning. Hasegawa et al. [26] designed a neural network to map from speech audio to 3D motion sequences. Kucherenko et al. [38] extended this work to learn a better representation of the motion, achieving smoother gestures as a result. Yoon et al. [58] learned a mapping from text to gestures using a recurrent neural network. Habibie et al. [25] applied Variational Autoencoders (VAEs) [37] for motion generation. They encoded a sequence of control signals into a latent representation using a CNN-based encoder, then used a Long Short-Term Memory (LSTM) decoder to synthesize motion. Speech-driven head-motion generation has similarly been approached by a variety of methods, such as Conditional Variational Autoencoders (CVAEs) conditioned on acoustic features in order to predict head pose [22], deep Bidirectional Long Short-Term Memory (BLSTM) networks used in [23, 24], and conditional Generative Adversarial Networks (GANs) [20] incorporating BLSTMs [54]. Similarly, facial expression generation has been explored by using BLSTMs [53] and GANs [12]. In another line of work, Karas et al. [34] trained a CNN-based neural network using speech together with a learned emotion representation as input in order to generate corresponding 3D meshes of faces with impressively little training data. Vougioukas et al. [57] used GANs for speech-driven facial animation from speech segments and a still face image.

2.3 Interlocutor-aware gesture generation

Our problem formulation is largely inspired by a recent method to model conversational dynamics for gesture generation [1]. Like in that work, we also model avatar behavior based on both the avatar’s own speech and the speech and motion of the interlocutor. One main difference between our work and that paper is that we model a different aspect of non-verbal behavior, namely facial gestures instead of hand gestures. Another important difference is that our method is not deterministic, but probabilistic. Their method is also based on data from motion capture, while our system uses regular videos as input and extracts features from these videos.

An example of a similar work that uses a probabilistic method is DyadGAN [29], which trained a conditional GAN to generate face images based on the interlocutor’s facial expressions. However, that work only produced a single image, and did not take the temporal aspect into consideration. Later work extended DyadGAN to generate sequences of interlocutor-aware facial gestures [48]. However, they did not use speech information, nor did they produce output parameters that can control a virtual agent. Feng et al. [19] presented a system using VAEs to generate facial gestures. They conducted experiments pitting their system against multiple baselines, e.g., copy-mimicry and random sequences, finding their system to outperform the baselines. Their system, however, is uni-modal and only uses facial information from the interlocutor, while our proposed method is multi-modal. Our system also relies on FLAME parameters for parametrization of the facial features.
as opposed to facial landmarks, freeing up our system to focus on only learning facial gestures and not lip-sync. Dermouche et al. [15] presented a system similar to Feng et al. but added the conversation state as additional conditional information, and also created a system usable in real time. They encoded the input using LSTMs while outputting FAPs. After conducting an experiment with the real-time system at a museum, their conclusion was that the system was preferred by the users if it smiled when the users smiled [15].

2.4 Normalizing flows
In this work we use normalizing flows [16, 49] for probabilistic modeling. This has several advantages over other methods such as VAE or GANs, as detailed in [27]. Essentially, normalizing flows offer the best of both worlds, combining the power and flexibility of GANs with easy training based on exact maximum likelihood, like in classic probabilistic models such as mixture densities [7].

The specific model we use is adopted from MoGlow [27], which introduced a normalizing-flow method called Glow [36] to the problem of motion generation. We describe the MoGlow method more in detail in Section 3. The method has been successfully applied to gesture generation [3], which inspired us to apply it to our problem as well. However, our system differs from MoGlow in several ways: 1) we use several modalities to condition the model, each encoded by a separate neural network; and 2) we apply the model to another task (interlocutor-aware facial-gesture generation), with weaker correlation between input and output. Another important aspect that sets us apart from both MoGlow and Ajuha et al.’s work [1] is that we we start from regular videos, thus not requiring data recorded using specialized motion-capture equipment.

3 SYSTEM ARCHITECTURE

3.1 Problem formulation
We frame the problem of generating interlocutor-aware facial gestures in the following way: given a sequence of speech features of the avatar $S^a = \{s^a_t\}_{t=1:T}$ as well as the interlocutor’s facial gestures $F^i = \{f^i_t\}_{t=1:T}$ and speech features $S^i = \{s^i_t\}_{t=1:T}$, the task is to generate a corresponding facial gesture sequence $f^a = \{f^a_t\}_{t=1:T}$ that the avatar might perform in the conversation.

3.2 Model foundations
The model we utilize to generate motion in this work belongs to the class of probabilistic generative models called normalizing flows. Normalizing flows are similar to generative adversarial networks (GANs) in that they generate output by drawing samples from a simple base or latent distribution $Z$ (here a standard normal distribution) and then transform these samples nonlinearly using a neural network $g$ such that the transformed output distribution $X = g(Z)$ matches that of the data. Different from the one-way neural networks in GANs, however, normalizing flows use invertible nonlinear transformations, so called invertible neural networks, for $g$. The approach gains power and expressivity by chaining together several simple nonlinear transformation, called steps of flow, analogous to the layers in a regular neural network. The invertibility makes it possible to use the change-of-variables formula to compute the exact likelihood of training data examples. Normalizing flow models (in practice, the weights of the invertible network $g$) can therefore be trained through gradient-based optimization minimizing the negative log-likelihood (NLL) of minibatch data, similar to likelihood maximization with classic probabilistic models such as hidden Markov models (HMMs) [51] and mixture density networks (MDNs) [7]. This means that flows can straightforwardly train generative models with an expressive power similar to GANs but without using a discriminator, thus avoiding the theoretical [45] and practical [42] issues that complicate GAN training. For a more in-depth treatment of normalizing flows please see the recent review paper by Papamakarios et al. [49].

The model in this paper is based on a specific normalizing flow transformation $g$ called Glow [36]. This choice allows both fast likelihood computation and efficient sampling from the learned distribution. Our model structure is similar to the MoGlow architecture used for autoregressive generation of pose sequences in locomotion [27] and gesture generation [3]. These papers also show how the nonlinear transformation $g$ – and thus the learned distribution $X = g(Z)$ – can be made to depend on conditioning information that affects the motion, including an external control signal. Specifically, MoGlow feeds the conditioning information as an additional input to the regular (one-way) neural networks contained inside each step of the normalizing flow (see [27]). We will use this control signal to create models of non-verbal behavior that are able to use the interlocutor’s speech and facial gestures. Like in MoGlow, we do not use any hierarchical structure in the generator, meaning that $L = 1$ in the language of Kingma et al. [36].

3.3 Proposed model overview
Our model generates facial gestures conditioned on the speech of the avatar as well as the speech and the facial features of the interlocutor. A graphical overview of the model is shown in Figure 2. The core of the model is the normalizing flow, which transforms Gaussian driving noise (shown below the model) into a distribution of facial expressions (shown on top of the model). In order to be able to generate smooth facial motion, the model is made autoregressive – it uses the avatar’s facial expressions from preceding frames as an extra conditioning to generate the next frame. The generated facial motion should be consistent with the avatar’s speech (although not the semantics) and hence our model is also conditioned on the avatar’s speech signal from previous $t^a_i$ time-steps. To enable generating appropriate behavior toward the interlocutor, the speech and facial motion of the interlocutor for the $t^i_s$ and $t^i_f$ time-steps, respectively, are used as additional conditioning for the normalizing flow. The proposed model hence learns to generate a distribution of appropriate facial gestures using multi-modal conditioning.

Since no previous facial expressions are available at test time, the model starts generation with a sequence of zero vectors standing in for the missing facial-gesture inputs.

Like in MoGlow [27] the conditioning information was concatenated with the other inputs to the networks inside the flow steps, but in our system each modality was encoded by a separate network (and later subjected to an additional transformation which was different for each step), as described in the next subsection.
3.4 Modality encoder

Four different inputs are used in our model to condition the output distribution: the interlocutor’s acoustic and facial features, as well as the agent’s own acoustic features and previous facial features (as autoregressive input to ensure continuity). How the acoustic and facial features were extracted is described in Section 4.1. Below we describe our modality encoders shown in Figure 2.

We experimented with different neural networks for encoding each modality: Multi-layer Perceptrons (MLPs), Recurrent Neural Networks (RNNs) and 1D-convolution networks (CNNs). We decided on the final configuration (RNNs) based on an initial hyperparameter search on the validation dataset. However, for the autoregression, the avatar’s previous facial features were passed into the normalizing flow model without any processing: simply as a concatenation of $t_{p_f}$. All other modalities were first encoded from sequences into fixed-length vectors using separate RNNs, specifically using Gated Recurrent Units (GRUs) [11]. We took both the hidden state and the final output from the GRUs to retain more information. For each step of the flow, all modality encodings were concatenated and then passed through a one-layer neural network with a LeakyReLU activation function. This transformation network was different in every step of the flow, resulting in different conditioning vectors in each step. The per-step conditioning information was used to influence the transformation in each step in the same way as in MoGlow.

3.5 Training scheme

We used teacher forcing without annealing or scheduled sampling. This means that the model always received the ground-truth autoregressive input during training instead of samples from the model, since the latter can make models converge on incorrect output [31].

We used the Adam optimizer [35] since it was used before to train similar systems [3, 27]. We also used learning-rate warm up, as is common for normalizing flows [36]. Different learning-rate schedulers were tested, but did not seem to impact the results.

In order for the model to listen more to the conditioning from the interlocutor we used a special training scheme based on negative learning [46]. The main idea is to not only minimize the loss of the training examples, but also maximize the loss of “wrong”, negative examples. There was a 0.1 probability to use a negative sample for each batch. Negative samples are created by shuffling both facial $F^t$ and speech conditioning $S^t$ in the conditioning information for the whole batch, so that each output sequence in the batch now has the conditioning information of a different sample. Temporal consistency was preserved – the mismatched conditioning was still a continuous sequence but from another example. Mathematically, a permutation of elements where no element appears in its original position is known as a derangement, but we will refer to such samples with deliberate incorrect conditioning as mismatched.

In order to make the model better at distinguishing between appropriate from inappropriate output motion, we want the log-likelihood for mismatched samples to be as small as possible. We
We used the MAHNOB Mimicry Database [6] to train and evaluate were used to determine bounding boxes for cropping and for the FLAME fitting. Cropped images were fed into RingNet [55] to esti-

3.6 Implementation and hyperparameters
Our implementation used the PyTorch-based [50] glow-pytorch github.com/chaiyujin/glow-pytorch as a base, adapted to PyTorch lightning [18].

The hyperparameter search used Optuna, [2], which identified the following hyperparameters that we used in our experiments for the proposed model: total conditioning dimensionality = 512, initial learning rate = $10^{-3}$, training sequence length = 80. The Glow parameters were: $K = 16$, number of hidden channels = 128. The hyperparameters of the modality encoders are given in Table 1.

4 DATA
We used the MAHNOB Mimicry Database [6] to train and evaluate the systems in this paper. It contains 11.5 hours of spontaneous dyadic conversations on different topics. The purpose of the corpus was to be able to study dyadic mimicry behavior. The data-gathering used a setup of 15 shutter-level synchronized cameras, two close-

4.1 Feature extraction
From the videos (one camera angle per person and session) we extracted 2,068,410 image frames at 25 fps. OpenFace [5] was then used in order to extract facial landmarks. The facial landmarks were used to determine bounding boxes for cropping and for the FLAME fitting. Cropped images were fed into RingNet [55] to esti-

4.2 Stimulus-generation pipeline
A number of processing steps, illustrated in Figure 3, were nec-

Table 1: Encoder hyperparameters. History indicates how many previous frames of a given modality that were used.

| Modality | Enc. Dim. | Enc. Type | History Len. | Dropout |
|----------|-----------|-----------|--------------|---------|
| $S^a$    | 128       | RNN       | 2            | 0.5     |
| $F^a$    | 256       | Concat    | 5            | 0       |
| $S^i$    | 256       | RNN       | 16           | 0.3     |
| $F^i$    | 256       | RNN       | 24           | 0.6     |

therefore switch the sign of the log-likelihood of negative exam-

Figure 3: Stimulus generation pipeline, showing how audio is transformed into lip motion and then combined with the model output and rendered.

through two optimizations outlined in [40]. The result was a 100D PCA expression vector, a 12D pose vector with rotations, and a 300D PCA shape vector. From the expression vector we used the 50 first components together with the neck (3D) and jaw (3D) ro-

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1 github.com/mmatl/pyrender
Table 2: Log-Likelihoods for the proposed model and its ablations on test sequences and mismatched versions thereof.

| System       | All correct | mismatched S$^a$ | mismatched S$^i$ | mismatched F$^i$ |
|--------------|-------------|-----------------|-----------------|-----------------|
| Our method   | 4.005 ± 144 | 4.005 ± 144     | 4.005 ± 144     | 253.22 ± 994.36|
| no-face      | 3.814 ± 240 | 3.814 ± 258     | -               | -               |
| no-speech    | 3.554 ± 67  | 3.554 ± 68      | -               | -               |
| no-neg-train | 3.869 ± 92  | 3.869 ± 93      | 3.869 ± 92      | 3.865 ± 97      |

5 EVALUATION

In this section we describe the objective and subjective experiments we conducted to evaluate our model, specifically an ablation study. We ablated several key components of the model, namely the modalities it used as input and the presence of the special training scheme with negative samples. The specific ablations we considered were:

- **no-face**: model not conditioned on the interlocutor’s facial features
- **no-speech**: model not conditioned on the interlocutor’s speech features
- **no-neg-train**: model trained without the negative samples described in Section 3.5

For each ablation we conducted a separate hyperparameter search on the validation dataset to find the optimal setup and re-trained the models from scratch using the best hyperparameters, to enable the most fair comparison.

In our ablation study we also evaluated how the models perform when they receive mismatched conditioning, as a way to understand to what extent the models takes the various multi-modal signals into account. We call the instances when the avatar’s speech was taken from another context “mismatched S$^a$”, when the interlocutor’s speech was taken from another context “mismatched S$^i$”, and when the interlocutor’s facial gestures were taken from another context “mismatched F$^i$”.

5.1 Objective evaluations

This section reports on the objective evaluations we performed. The interpretation of the results is discussed in Section 6.

It is difficult to evaluate the quality of facial gestures objectively, and it is even harder to objectively evaluate whether or not facial gestures are adapted to the interlocutor. Calculating distance from recorded “ground truth” motion is not meaningful, as a multitude of different gestures can be appropriate even if the conditioning input is fixed. We instead considered the following three objective measures in our experiments:

5.1.1 Likelihood. Since normalizing flows enable direct probabilistic inference, we are able to calculate the log-likelihood of test data under our model. The test data should have high likelihood only if we model the data distribution well.

We evaluated log-likelihood for the proposed model and its ablations for unmodified test sequences as well as mismatched sequences as defined above. The average values along with their standard deviations are given in Table 2.

5.1.2 Jerk. The rate of change of acceleration, or jerk, is a common measure of motion smoothness and has been used to evaluate the quality of non-verbal behavior before [38]. We evaluated the average jerk and its standard deviation in Table 3.

5.1.3 Range of the motion. To quantify the amount of variety in the gestures generated by the different models, we evaluate their range of motion by calculating the standard deviation of the facial vector over the test dataset. Results are presented in Table 4.

5.2 Subjective evaluation setup

Five experiments were conducted in order to evaluate human perception of the produced facial gestures. The studies were all carried out on Amazon Mechanical Turk (AMT). The five experiments were designed to answer the following five questions:

1. Can participants discern appropriate facial gestures using our visualization?
2. Does our model take interlocutor input into consideration?
3. What multi-modal input was most important, speech or face (evaluating face)?
4. What multi-modal input was most important, speech or face (evaluating speech)?
5. Does the training scheme with negative samples significantly improve the perceptual quality of output gestures?

5.2.1 Procedure. Every participant was first provided instructions and then completed a training phase to familiarize themselves with the task and interface. The training consisted of three items showing the participants what kind of videos they may encounter during the study. Each participant was then asked to evaluate video pairs, this was done in a similar fashion as described in [19]. In all studies participants compared two videos, each containing two virtual characters interacting with each other (see Figure 1). The participants were always asked to evaluate only the avatar on the right, since it was the only one that was manipulated: the left avatar – the interlocutor – was always the same between both videos, and its movements reflected the same segment of ground-truth motion in the data. The videos were presented side by side and could be replayed separately as many times as desired. For each pair, participants indicated which video they thought best corresponded to the given question and there was also an option to state that

Table 3: Average absolute jerk (third derivative of position) for ablations and matched/mismatched conditioning inputs.

| System       | All correct | mismatched S$^a$ | mismatched S$^i$ | mismatched F$^i$ |
|--------------|-------------|-----------------|-----------------|-----------------|
| Our method   | 0.26 ± 0.27 | 0.26 ± 0.27     | 0.26 ± 0.27     | 0.26 ± 0.27     |
| no-face      | 0.28 ± 0.31 | 0.28 ± 0.3      | 0.28 ± 0.3      | -               |
| no-speech    | 0.22 ± 0.23 | 0.22 ± 0.23     | -               | -               |
| no-neg-train | 0.24 ± 0.26 | 0.24 ± 0.26     | 0.24 ± 0.26     | 0.24 ± 0.26     |
| ground truth | 0.14 ± 0.19 | -               | -               | -               |

Table 4: Range-of-motion results. The data was standardized so that the mean was 0 and the standard deviation was 1. Reported values are standard deviations of sampled motion.

| System       | All correct | mismatched S$^a$ | mismatched S$^i$ | mismatched F$^i$ |
|--------------|-------------|-----------------|-----------------|-----------------|
| Our method   | 1.02        | 1.02            | 1.02            | 1.02            |
| no-face      | 0.94        | 0.94            | -               | -               |
| no-speech    | 0.9         | 0.9             | -               | -               |
| no-neg-train | 0.89        | 0.89            | 0.89            | 0.9             |
| ground truth | 0.92        | -               | -               | -               |
they perceived both videos to be equally appropriate. The question we asked was always the same across all of the experiments and similar to that used by Ahuja et al. [1]: “Which of the two characters on the right side of each video has the most appropriate behavior in response to the character on its left?”

All subjective tests used a binomial sign test with Bonferroni correction for the five studies. Ties were excluded.

5.2.2 Stimuli. Since the goal was to evaluate facial gestures, audio was removed, but lip-sync, based on the original audio for each character, was retained and was the same between both videos in each evaluated pair. The avatars were placed side by side and facing forward. To be precise, the orientation would be adjusted such that the 3D avatar would face the viewer when the original talker was facing the other interlocutor in the original interaction. The neck rotation was subtracted from the eyes, giving the sensation of the avatar looking straight at the viewer even when turning its head. Head shape, gender and skin color (see Figure 1 for an example) were randomized but kept constant for each video segment across all experiments. Which of the two conversation parties in the original ground-truth interaction that was selected as the interlocutor, and thus placed on the left, was based on who spoke the most in that segment, determined by summing the VAD voice activity.

22 video pairs were evaluated in each experiment, except for Experiment 1, where 64 video pairs were evaluated (34 mimicry and 30 non-mimicry segments) and each participant evaluated 10 random pairs of each type. Segments were randomly counterbalanced. Segments varied in duration from one to eight seconds, based on the duration of the original mimicry annotations. All experiments used the same segments, except Experiment 1 which had additional segments as above. A few randomly-selected examples generated using our method are available at vimeo.com/showcase/7219185.

5.2.3 Participants. All participants were recruited through AMT and were only allowed to participate once in any of the studies. The participants had to have an acceptance rate of at least 98% and completed over 10,000 previous HITs to be eligible for our study. We used attention checks to filter out inattentive participants. For workers to perceive a difference between the actual facial gestures we evaluated if our stimulus-generation methods allowed online correction for the five studies. Ties were excluded. If they failed any of these attention checks. The other three attention checks comprised pairs presenting the exact same video twice and were placed at the 7th, 10th, and the 15th trial-position for all experimental sessions. Here, an attentive rater should answer “no difference”. Participants were excluded if they failed any of these attention checks.

5.3 Results of subjective evaluation

The results for Experiment 2,3,4, and 5 are shown in Figure 4.

5.3.1 Experiment 1: Matched and mismatched ground truth. First we evaluated if our stimulus-generation methods allowed online workers to perceive a difference between the actual facial gestures (ground truth condition) and avatar gestures taken from another point in time in the same interaction but with the same person (mismatched condition). We recruited 30 participants (14 female, 16 male), all from the USA. Their mean age was 37.4 with a std of 11.1.

We conducted a binomial sign test with Bonferroni correction excluding ties to analyze the responses separately for the two types of the stimuli: those for the “mimicry” segments and those for the “non-mimicry” segments. The ground truth videos were preferred over the Mismatched ones for mimicry segments ($p < 0.001$). There was no statistical significance for the non-mimicry segments ($p=1$). These results indicate that online workers can indeed distinguish the Mismatched facial gestures from the ground truth, but only in segments where that difference is salient, e.g., if the conversation parties display strong non-verbal interactions such as mimicry. Given this result we concentrated our remaining evaluations on mimicry segments, since they provided for the clearest distinction between appropriate and inappropriate agent behavior. As the non-mimicry segments did not produce a statistically difference they were excluded from remaining studies. Furthermore, since our model required 24 frames (0.96 s) of initialization data, only 22 samples could be used for the remaining experiments.

5.3.2 Experiment 2: Matched and mismatched proposed model. In the second experiment we evaluated whether the proposed model actually uses the interlocutor’s input when generating facial gestures. To this end, we shuffled the conditioning information like before, creating mismatched stimuli where the conditioning information from the interlocutor was always taken from a different sample than the motion used by the interlocutor avatar in the video (but still from the same session and the same person). We compared the proposed model’s facial gestures using normal test sequences versus those using mismatched sequences. This use of matched and mismatched samples has the advantage that the quality of the motion is the same across the conditions seen in the videos (since all avatar motion was generated from the same trained model); only the appropriateness of the motion may differ between the two.

We recruited 30 participants (22 male, 8 female). The majority (29) were from the USA. Their mean age was 33.7 with a std of 6.9. The test showed a statistically significant difference between the model output on matched and mismatched test sequences. Specifically, there was a preference towards the matched sequences ($p = 0.032$).
5.3.3 Experiment 3: Ablating facial gestures. In this experiment we compared the proposed model (proposed condition) against the ablation where the interlocutor’s facial gestures was not available to the model (no-face condition). We recruited 30 participants (19 male, 10 female, 1 non-binary), of which 29 were from the USA. Their mean age was 37.3 with a std of 9.4. The test showed a statistically significant preference for the proposed model over the no-face ablation ($p < 0.001$).

5.3.4 Experiment 4: Ablating speech. In this experiment we compared the proposed model (proposed condition) against the ablation where the interlocutor’s speech was not available to the model (no-speech condition). We recruited 30 participants (16 male, 13 female, 1 non-binary), of which 29 were from the USA. Their mean age was 36.6 with a std of 8.7. The test showed a statistically significant preference for the no-speech ablation ($p < 0.001$).

5.3.5 Experiment 5: Negative sample training. In this experiment we compared the proposed model (proposed condition) against the same model without any negative samples during training. (no-negative-training condition).

We recruited 30 participants (17 male, 13 female), of which 28 were from the USA. Their mean age was 38.7 with a std of 12.6. The test showed a statistically significant preference for the model trained without the special training scheme ($p = 0.003$).

6 DISCUSSION

The purpose of Experiment 2 (Section 5.3.2) was to see if our method can leverage the multi-modal input to generate more appropriate motion in response to the interlocutor. We found a significant preference for when the model outputs facial gestures relevant to the context, as opposed to a random context, indicating that we successfully generated interlocutor-aware facial gestures. This result is in line with the findings from Experiment 1, where it was shown that evaluators can indeed distinguish – and furthermore prefer – non-verbal behavior which is dependent on the interlocutor over any random (coherent) facial gestures.

Experiments 3 and 4 were designed to assess the relative importance of different interlocutor input modalities. Experiment 3 (Section 5.3.3) considered removing the interlocutor facial information. This made the model perceptually significantly worse. In addition, this no-face condition gave the jerkiest motion (Table 3) and gave likelihoods that were significantly affected by mismatched speech information (Table 2), suggesting that, lacking facial information, the model instead became more attuned to the interlocutor’s speech, possibly to the point of overfitting.

If we instead removed the interlocutor speech input (Experiment 4, in Section 5.3.4), the resulting ablation performed significantly better than the proposed model. This suggests that the facial information is the most important for the model. It is surprising that the model conditioned on facial information alone was better than the one conditioned on face and speech together. Speculatively, this might be due to the type of speech features used, and experimenting with more speaker-independent speech representations would be interesting for future work. Additionally, we can see that both the no-speech and no-neg-train conditions had lower range of motion than the ground truth, indicating that they were not as animated and closer to the mean face. While being closer to the mean face might yield a less expressive and animated result, it also provides less room for making mistakes that the evaluators are sensitive to. Finally, it is important to note that there was no audio in the evaluated stimuli, which may have affected the results.

There is an intriguing disparity between the likelihood numbers in Table 2 – where negative training helped models learn to more effectively assign probability mass to motions matching the interlocutor (as opposed to non-matching motion) – and the subjective results from Experiment 5, which found that not using negative samples in the training was perceived significantly better. While negatively-trained models clearly were able to learn to distinguish well between scenarios with matched and mismatched modalities, they do not appear to have leveraged this to generate more appropriate motion in matched setups. However, it is also well known that likelihoods and human ratings are sensitive to different modeling aspects (see, for instance, [56]). Thus higher likelihood does not necessarily mean better perceptual quality, and our findings here are likely another reflection of that fact.

For the jerk and range-of-motion results (Tables 3 and 4) we see that models were generally unaffected by being provided mismatched sequences. This is probably due to the models learning the low-level movements from the autoregression, with the conditioning information operating on a higher level. We infer that our approach is able to generate similarly smooth motion regardless of whether the different multi-modal inputs (the interlocutor facial features and speech features) are taken from a different context or not. However, not including the interlocutor’s facial information resulted in a model with the highest jerk, and we again conclude that the facial features seem to be the most important in this task.

The proposed method had a range of motion close to 1 on test data, somewhat exceeding the ground truth value of 0.923. This might be due to the fact that the synthetic motion is jerrier than natural motion, inflating the range of motion somewhat, and we observed similar trends of the proposed method exhibiting a slightly greater than natural range of motion also when synthesizing and comparing against motion in the training data.

6.1 Limitations

A limitation of this work is the fact that we are evaluating multi-modal interactions that contain speech, but without revealing that speech to the evaluators. This was a deliberate choice, as we in a pre-study on mismatched ground-truth motion found that participants otherwise tend to assign an inordinate significance to the linguistic content and how the avatar moves and behaves in relation to that content. Since the presented method does not attempt to model semantics, removing the speech would make it less likely that evaluators assign spurious semantic meaning to the gestures, and instead force them to evaluate the motion in a non-semantic way. We believe that this limitation would be most likely to affect evaluators’ assessments of the impact of the speech modalities on the motion, such as the results of Experiment 4.
7 CONCLUSION

We have presented a method for probabilistic and interlocutor-aware facial-gesture generation based on multi-modal inputs. Experiments found that human raters significantly preferred facial gestures generated in response to the interlocutor over mismatched facial gestures that did not take the interlocutor into account. This shows that the proposed approach managed to leverage the multi-modal input to generate better gestures. We evaluated our system on mimicry segments due to their perceptual saliency, but it should be stressed that no information relating specifically to mimicry was used during training. The subjective appropriateness of generated motion decreased significantly when information about the interlocutor’s facial gestures was omitted, suggesting that this modality is of major importance to the task.

Future work should investigate the use of other parametrizations of multi-modal signals, especially speech representations, and various ways of incorporating them into the model. It would also be highly interesting to investigate how this method would work in a real-time interaction with a user.

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