Responsive Listening Head Generation: A Benchmark Dataset and Baseline

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Abstract

Responsive listening during face-to-face conversations is a critical element of social interaction and is well established in psychological research. Through non-verbal signals response to the speakers’ words, intonations, or behaviors in real-time, listeners show how they are engaged in dialogue. In this work, we build the Responsive Listener Dataset (RLD), a conversation video corpus collected from the public resources featuring 67 speakers, 76 listeners with three different attitudes. We define the responsive listening head generation task as the synthesis of a non-verbal head with motions and expressions reacting to the multiple inputs, including the audio and visual signal of the speaker. Unlike speech-driven gesture or talking head generation, we introduce more modals in this task, hoping to benefit several research fields, including human-to-human interaction, video-to-video translation, cross-modal understanding, and generation. Furthermore, we release an attitude conditioned listening head generation baseline. Project page: https://project.mhzhou.com/rlld.

1. Introduction

Communication is one of the most common activities that people engage in their daily lives. It has been well studied by sociologists and linguists for many years [5, 24, 34, 38, 44, 46]. In face-to-face communication [29], the speaker transmits the verbal and non-verbal messages explicitly, and the listener receives the message and provides real-time responsive feedback to the speaker through non-verbal behavior (e.g., nod, smile, shake, etc.). Generating proper responsive listening behavior is essential for various applications such as digital avatars and social robots.

As pointed out by Hunsaker et al. [2], listening behavior style can be categorized into four categories, i.e., non-listener, marginal listener, evaluative listener, and active listener. Active and responsive listening is the most effective one, and it also plays a key role in successful communication [36, 41–43]. It requires the listener to focus completely on what a person is saying and listen carefully while showing some visual reactions to the speaker. These reactions can feedback the speaker about whether the listener is interested, understand, and agree with the speech.

Although the static images, repeated frames, or scripted animations are often used to synthesize listeners in the industry, they are often rigid and not realistic enough to respond to the speaker appropriately in real-time. According to the concepts from social psychology and anthropology, listening is a function-specific [18] and also conditioned (learnable) behavior [4]. First of all, common visual patterns do exist for listeners to express their views, e.g., symmetrical and cyclic movements were employed to signal ‘yes’, ‘no’ or equivalents; narrow linear movements occurred in phase with stressed syllables in the other’s speech; wide, linear movements occurred during pauses in the other’s speech. Even the duration of eye blinks of the listener is perceived as communicative signals in human face-to-face interaction [23]. And then, these visual patterns of the listener are mainly influenced by two kinds of signals: (1) The attitude of listener [21]. Different attitude of the listener results in different expression or facial motions, e.g., attitude of agree is meant by a nod, as well as accept. attitude of disbelieve is represented by the combination of head tilt and frown. (2) The signals from the speaker. According to the findings of the previous research [10, 16, 35], listening behavior is speaker motion captured, together with the audio being listened to, i.e., the flow of movement in the listener may be rhythmically coordinated with the speech and movements of the speaker [28]. These psychological and ethological studies motivate us to propose a data-driven method for modeling the responsive listening behaviors.

Recently, some works were proposed to model the realistic information presentation from speaker. As shown in Fig. 1, speech to gesture generation [17] learns a mapping between the audio signal and speaker’s pose. Speech to lip generation task [39] aims to refine the lip-synchronization of a given video input. Talking head synthesis [11, 47, 55] tries to generate a vivid talking video of a specific speaker with facial animations from a still image and a clip of au-
dio. However, these speaker-centered tasks focus on exporting information more accurately to receivers through visual, verbal, and speech signals while overlooking the listener behaviors modeling, which is an essential part of future intelligence assistance and the next generation of human-computer interaction.

In this paper, we first define the responsive listening head generation task. Different from the previous speaker-centered tasks, which can be regarded as audio signals driven cross-modal translation (inputs are audio segment, outputs are face lip, expression, or gesture), responsive listening head generation, as shown in Fig. 1 (d), is a more complex task since it needs a deep understanding of the combination of the speaker’s facial signals and voice, then generating the listener’s head motion and facial expression respecting the correlation between speaker and active listener in real-time. Furthermore, unlike the emotion-driven talking head synthesis, attitude conditioned listening head synthesis needs a more precise controller for presenting the subtle changes of facial micro-expressions.

To address this, we construct a high-quality speaker-listener dataset, named RLD dataset, by capturing the high-definition video data from public conversations (e.g., online interview in news program) between two people on the same screen containing frontal faces. The data strictly follows the principle that a video clip contains only uniquely identified listener and speaker, and requires that the listener has responsive non-verbal feedback on the content of the conversation. We annotate the listener at three different attitudes. In total, our RLD dataset contains over one-hour video clips of 76 listeners responding to 67 speakers.

Together with the dataset, we propose an attitude conditioned responsive listening head generation baseline. As we know, the previous speaker-centered tasks are usually modeled in an idiosyncratic way (different speakers are modeled independently). However, listening behavior patterns are typically consistent with the speaker’s signals. Thus we decouple the identity features from the listener and focus on learning the general motion patterns of responsive listening behaviors. By treating the responsive listening head generation task as a video-to-video translation task, a sequence-to-sequence architecture is designed to sequentially decode the listener’s head motion and expression, conditioned by the given attitude label and the encoded speaker features.

2. Related Works

**Active listener** Active listening is an effective communication skill that not only means focusing fully on the speaker but also actively showing the non-verbal signals of listening with attitude. Usually, the active listener would mirror some facial expressions used by the speaker or shows more eye contact with the speaker. Active listening have shown its positive effects in many areas, such as teaching [26], medical consultations [15], team management [37], etc. In this paper, we aim to generate an active listener that could provide responsive feedback, the listener would understand the speaker’s verbal and non-verbal signals first and then give proper feedback to the speaker.

**Speaker-centered video synthesis** Given time-varying signals and a reference still image of the speaker, the talking head synthesis task aims to generate a vivid clip for the speaker with the time-varying signals matched. Based on the different types of time-varying signals, we can group these tasks into two groups: 1) audio-driven talking head synthesis [11, 39, 52], 2) video-driven talking head synthesis [3, 49]. The goal of the former one is to generate a video of the speaker that matches the audio. And the latter one is to generate videos of speakers with expressions similar to those in the video. Both tasks focus on only one speaker and transfer similar patterns from other signals to generate a video of that speaker. They don’t perceive but memorize. This differs from our tasks: the “listener” is forced to perceive the speaker’s visual and audio signals and make an active response. Our task does not focus on only a single person or transfers face expression and...
slight head movements from another person; we have two roles: listener and speaker, and the listener should actively respond to the speaker with non-verbal signals.

Many applications and research papers have focused on speaking, while the “listener modeling” is seldomly explored. This is perhaps caused by the speaker patterns are more explicit to capture. Gillies et al. [16] first propose the data-driven method that can generate an animated character that can respond to speaker’s voice. This lacks the supervision of speaker visual signals, which is incomplete for responsive listener modeling. And this method can not be applied to realistic head synthesis. Later, Heylen et al. [20] further studied the relationship between listener and speaker audio/visual signals from cognitive technologies view. ALICO [8] corpus was proposed to focus on the behaviors analysis of active listeners. But it has not been made public and also not constructed from the real scene conversations. Moreover, the main objective of ALICO is for psychology analysis, the data mode of that dataset is vastly different from the audio-video corpuses in computer vision area. In this work, we first define the task of responsive listening head generation and construct a public RLD dataset for this task. Meanwhile, a baseline method is proposed for listening head synthesis by perceiving both speaker’s audio/visual signals and preset attitude.

3. Task Overview

We present Responsive Listening Head Generation, a new task that challenges vision systems to generate listening head actively responding to the speaker’s face or/and audio in real-time. In special, we need to understand the head motion, facial expression, including eye blinks, mouth movements, etc., of the input speaker video frame, and simultaneously understand the speaker’s voice, then synchronously generate the active listening face video conditioned by the given attitude.

Given input video sequence $V^s_t = \{v^s_1, \cdots, v^s_t\}$ of a speaker head in time stamps range from $\{1,..., t\}$, and an corresponding audio signal sequence $A^s_t = \{a_1, \cdots, a_t\}$ of the speaker, our listening head synthesis aims to generate a listener’s head $v^l_{t+1}$ of the next time stamp, which can be represented as:

$$v^l_{t+1} = G(V^s_t, A^s_t \mid v^l_1, e),$$  \hspace{1cm} (1)

where $v^l_1$ is the reference head of the listener, $e$ denotes the attitude of the listener. The whole generated listener video $V^l_{t+1}$ can be denoted as the combination of $\{v^l_2, \cdots, v^l_{t+1}\}$.

Listening attitude definition During conversation, after perceiving the signals from the speaker, the listener usually reacts with an active, responsive attitude, including epistemic attitudes such as agree and disagree or affective attitudes such as liking and disliking. In this work, we group the attitudes to three categories: positive, negative and neutral. Positive attitude consists of agree, like, interested. Conversely, negative attitude consists of disagree, dislike, disbelieve, not interested.

In general, attitude potentially guides the listener’s behavior and consequently affects the conversation. Also, different attitude results in different facial expressions and behaviors of the listener [21]. For example, to mean like a smile appears as the most appropriate signal, a combination of smile and raise eyebrows could be a possibility for interested, disagree can be meant by a head shake, dislike is represented by a frown and tension of the lips, etc. A listener in our constructed dataset with different attitudes is illustrated in Fig. 2.

Feature extraction In this paper, we extract the energy feature, temporal domain feature, and frequency domain feature of the input audio; and model the facial information with head pose using 3DMM coefficients.

For the audio, we extract the Mel-frequency cepstral coefficients (MFCC) feature with the corresponding MFCC Delta and Delta-Delta feature. Besides, the loudness and zero-crossing rate (ZCR) are also embedded into audio features $s_i$ for each audio clip $a_i$. The audio feature extracted from $A^s_t$ can be denoted as $S^t = \{s_1, \cdots, s_t\}$.

We leverage the state-of-the-art deep learning-based 3D face reconstruction model [14] for the videos to get the 3DMM [6] coefficients. Specially, for each image, we can get the reconstruction coefficients $\{\alpha, \beta, \delta, p, \gamma\}$ where denotes identity, expression, texture [9, 25], pose and lighting [40], respectively. Further, we distinguished the 3D reconstruction coefficients into two parts: $I = \{\alpha, \gamma\}$ to represent relatively fixed, identity-dependent features, and $m = (\beta, p)$ to represent relatively dynamic, identity-independent features. The identity-independent feature extracted from speaker videos can be denoted as $M^s_i = \{m^s_i, \cdots, m^s_i\}$, where $m^s_i \in \mathbb{R}^{1 \times C_v}$ is the expression and pose feature of 3D reconstruction coefficients for the $i$-th frame $v^s_i$, where $C_v = |\beta| + |p|$.

Task definition To ignore identity-dependent features and learn general listener patterns that can be adapted to multiple listener identities, we use only the head motion and facial expression feature $m$ for responsive listening
head generation model training, and then adapt the identity-dependent features $I$ of different listener identities for visualization and evaluation. Thus our listening head synthesis task can be formulated as:

$$m_{t+1}^l = G_m(M_{t}^l, S_{t}^l | m_{t}, e),$$
$$v_{t+1}^l = G_v(m_{t+1}^l, I_{t}^l, v_{t}^l),$$

where $m_{t+1}^l$ is the dynamic feature predicted for listener’s head, and $I_{t}^l$ denotes the identity-dependent features of the given listener. In a real implementation, we use $T$ frame of speaker’s audio and video for responsive listening head generation model training.

The 3D face rendering technology $G_v$ has been well studied in many recent related works [30, 52]. Moreover, the face rendering models are usually identity-specific, so one needs to train the rendering model separately for each listener. To highlight the properties of responsive listening head synthesis task, and decouple the critical factor in this task, our proposed responsive listening head synthesis model primarily focuses on the motion-related and identity-independent 3D facial coefficients prediction task $G_m$.  

4. Data Collection

We construct a dataset for responsive listening head generation by capturing conversational video clips from YouTube containing two people’s frontal faces. A valid video clip is required to meet the following conditions:

- The screen contains only two people, and one of them is speaking while the other one is listening carefully.
- The frontal faces of both of two people are clearly visible. The facial expression is natural and stable.
- The listener actively responds to the speaker in a dynamic and real-time manner.

The annotators are asked to accurately record the start and end time of each valid clip, label the position of the speaker (left or right of the screen) and identify the attitude of the listener in the video. Cross-validation is applied among at least three annotators for each candidate video clip to verify the quality of annotations. For each valid clip, we use the MTCNN [53] to detect the face regions in each frame, and then crop and resize the detected face regions to 384×384 resolution image sequence for model training and evaluation, as shown in Fig. 3.

Table 1 shows the statistical information of our annotated responsive listening head generation dataset RLD. The proposed dataset contains rich samples of 394 video clips. We normalize all videos to 30 FPS, forming more than 0.1 million frames in total. Due to the difficulty of obtaining high-quality videos with two people’s frontal faces, especially for the negative attitude, our dataset contains 23 negative clips. But according to the qualitative and quantitative results in Sec. 5.3, the scale of RLD is sufficient for generating reasonable listening patterns for different identities. Moreover, our dataset has following properties:

- **High quality** All raw videos are of high resolutions (at least 1920×1080 resolution), so that the subtle differences between different attitudes and changing moods are well preserved. And audios are in 44.1 kHz/16 bit such that the speech-related features can be well preserved, too.

- **High diversity** Our dataset contains various scenarios, including News interviews, entertainment interviews, TED discussions, variety shows, etc. These diverse scenarios provide rich semantic information and various listener patterns in different situations. The video clips length ranges from 1 to 71 seconds.

- **Realtime and interactivity** Different from the existing talking head video datasets [1, 12, 32, 47, 51] which aim to generate head or face in synchronization with the audio signals, our dataset focus on the face-to-face response. These responses are generated by jointly understanding the speaker’s audio, facial, and head motion signals, then adapting to different listener heads. It matters about mutual interaction rather than a monologue.
5. Responsive Listening Head Generation

Based on RLD dataset, we propose a responsive listening head generation baseline. The overview of our approach is illustrated in Fig. 4.

5.1. Model architecture

According to the psychological knowledge, an active listener tends to respond to the speaker based on the speaker’s audio signals [28] and visual signals [10, 16, 35] comprehensively. And at a given moment, the listener synthesizes information from the speaker of that moment as well as information from history and adopts a certain attitude to present actions in response to the speaker. Thus, the goal of our model is to estimate the conditioned probability $p(\mathcal{M}_t, \mathcal{S}_t, m^I_t, e)$, where the $\mathcal{M}_t$ and $\mathcal{S}_t$ are time-varying signals which the listener should respond to, and the reference listener feature $m^I_t$ and attitude $e$ constrain the pattern of the entire generated sequence.

Inspired by the sequence-to-sequence model [45], a multi-layer Long-short Term Memory (LSTM) [22] is applied for modeling the time-sequential information of conversation. Unlike talking head generation [11, 47, 52, 55], which accepts an entire input of audio and then processes it using a bidirectional LSTM or attention layer; in our scenario, the model $G_m$ receives the streaming input of the speaker where future information is not perceived.

For the speaker feature encoder, at each time step $t$, we first extract the audio feature $s_t$ and the speaker’s head and facial expression representation $m^I_t$, then apply non-linear feature transformations following a multi-modal feature fusion function $f_{am}$ to get the encoded feature of speaker.

To make sure the listener can respond in a certain attitude and generate a more natural head motion and expression changes, we embed the one-hot attitude $e$ and the representation of reference listener $m^I_t$ together, then set the embedded feature vector as the initial hidden state $h_1$ for the LSTM based listener behavior decoder. At each time step $t$, the LSTM cell takes the speaker’s fused feature $f_{am}(s_t, m^I_t)$ as input and generate the hidden state $h_{t+1}$ and cell state $c_{t+1}$ for sequence memory controlling. Finally, a listener motion decoder $D_m$ is used to decode $h_{t+1}$ to $m^I_{t+1}$, which contains two feature vectors, i.e. $\beta^l_{t+1}$ indicating the expression and $\beta^l_{t+1}$ indicating the head rotation and translation. Our responsive listening head generator supports an arbitrary length of speaker input. The procedure can be formulated as:

$$\beta^l_{t+1}, \beta^l_{t+1} = D_m(h_{t+1}, c_{t+1}, f_{am}(s_t, m^I_t)).$$

(3)

Fixing the overall pipeline of this responsive listening head generation baseline, the key technologies is specialized in the formulation of $f_{am}$ and $D_m$. There are already many related works studying the audio-visual feature fusion for various tasks, e.g., speaker identification [50], emotion recognition [54], activity recognition [27], etc. Furthermore, the head motion decoder is also well studied in talking-head synthesis [13, 48]. In this paper, without going deep into the methodology of these specific modules, we focus on the overall pipeline of our proposed task. Thus we simplify the operation of $f_{am}$ and $D_m$ as the feature concatenation and fully-connected layer with non-linear activation, respectively.

For the optimization, with the ground truth listener patterns $\mathcal{M}_T = [m^I_1, m^I_2, \cdots, m^I_T]$, we drop the last prediction $m^I_{T+1}$ due to the lack of supervision signals and use $L_2$ distance to optimize the training procedure:

$$\mathcal{L}_{gen} = \sum_{t=2}^{T} \| \beta^l_t - \hat{\beta}^l_t \|^2 + \| p^l_t - \hat{p}^l_t \|^2.$$  

(4)

Moreover, a motion constraint loss $\mathcal{L}_{mot}$ is applied to guarantee the inter-frame continuity across $\mathcal{M}_T$ is similar...

Figure 4. The overall pipeline of our responsive listening head generation baseline. The speaker encoder aims to encode the head motion, facial expression and audio features. Starting from the fused feature from reference listener image and predefined attitude, the listener decoder receives signals from speaker encoder in order of time sequence and predicts the head motion and facial expression features. These features are adapted to reconstruct the 3DMM coefficients with the reference listener’s identity-dependent features.
for zero-shot listening head generation to ensure our model’s effective in-domain data, and iii) out-of-domain (OOD) test set $D_{ood}$ for zero-shot listening head generation to ensure our learned listening motions are generic and transferable. In this case, all identities in the test set have appeared in the training set, while the identities in the OOD set have never appeared in the training set. That is, given a function mapping $\phi : S \rightarrow I$ that can get all identities $I$ from the dataset $S$, there exists two rules: $\phi(D_{ood}) \subseteq \phi(D_{train})$ while $\phi(D_{ood}) \not\subseteq \phi(D_{test})$.

We extract 44 acoustic features for audios, including 14 MFCC, 28 MFCC-Delta, ZCR and loudness. Our listening head generation model is trained with AdamW [33] optimizer with a learning rate of $1 \times 10^{-3}$ (decayed exponentially by 0.8 every 30 epochs), $\beta_1 = 0.9$ and $\beta_2 = 0.999$, for 130 epochs. For all experiments, we set hyper-parameter $\omega$ as 1.0, and the length of training sequence $T$ as 32.

### 5.3. Experimental results

#### Qualitative results

Given $D_{test}$ and $D_{ood}$, we generate listener videos for different attitudes. We randomly select two 32-frame head sequences from these two sets and then downsample them to 16 images to qualitatively visualize the generated results and the ground truth video. The results are shown in Fig. 5. We can find that our model is generally able to capture listener patterns (e.g., eye, mouth, and head motion, etc.), which may differ from the ground-truth while still making sense.

Further, the model is able to present the visual patterns of listeners under different attitudes. For the results in $D_{test}$, we can see that though a neutral attitude can also laugh (frame 2–8), it maintains a shorter time than a positive attitude (frame 2–16). And for the negative attitude, the listener doesn’t focus on the conversation; they look to the lower side of the screen at frames 10, 16, 22, and 30.

Finally, we also have relatively good generative results on the $D_{ood}$. The positive listener smiles at frames 6–14, the negative listener frowns and shows a negative mouth shape throughout the process, in sync with the typical behaviors introduced in [21]. There are also slight motion variations for the negative listener to present the distant look, and the neutral listener maintains a relatively calm expression but with regular head movements. The results on $D_{ood}$ also verify the listener patterns are generalizable and transferable.

#### Quantitative results

We assess the quality of the generated listening heads from feature-level and image-level respectively. For the feature-level assessment, we use the $L_1$ distance between the generated features and the ground-truth features (FD) to ensure the predicted head and expression coefficients are similar to the ground-truth ones. And for the image-level assessment, we use the Fréchet Inception Distance (FID) [19] to evaluate the quality of generated images. Since we don’t train the 3D face rendering network $G_v$, we measure the FID on plain face mesh.

Since we use the parametric face model [25], the results are ensured to be clear, the Cumulative Probability of Blur Detection (CPBD) [7] metric and Peak Signal-to-Noise Ratio (PSNR) is not used. The results are shown in Table 2. The averaged FD (pose) and FID on $D_{test}$ are better than $D_{ood}$, which is caused by the identity bias and information loss during feature transfer.
Figure 5. Two groups of example listening head generated by our proposed baseline method. The ground-truth (GT) listener in the upper one has positive attitude, and this speaker-listener pair is randomly sampled from $D_{test}$. The lower one is neutral attitude originally, randomly sampled from $D_{ood}$. The Line 6,7,8 and Line 10,11,12 show our generated listening head results conditioned by three different attitudes. Frame 0 is the reference listening head. The triangles indicate significant changes. Upper right yellow: sightline changes with eye movements; Lower left green: head motion; Lower right red: the representative frames in each row; Upper left purple: the frames (in column) with significant difference across different attitudes. More results are included in supplementary materials.

**User study** Since responsive listening head modeling is a user-oriented task, it is essential to conduct user studies for evaluation. For $D_{test}$ and $D_{ood}$, we had 11 volunteers doing two blind tests: 1) **Best Matching Test.** Given the 5-tuple of $\langle$attitude, speaker audio, speaker video, ground-truth listening head, generated listening head$\rangle$ that randomly sampled from $D_{test}$ and $D_{ood}$ (the ground-truth and generated listening heads were randomly ordered in the 5-tuple), the volunteers were asked to pick which one is the best listening head. 2) **Attitude Matching Test.** Given the randomly shuffled listening heads generations conditioned by three different attitudes for each identity. The volunteers were asked to identify one attitude for each listening head. In these two tests, the volunteers made decision by considering whether the listener behave reasonably, naturally, and dynamically to the speaker, and whether the listener holds a correct response to the given attitude.

For the first user-study, each volunteer was asked to check 30 user study samples. As shown in Table 3, the overall mean and variance statistics of the “better one” amount are gathered for analysis. In $D_{test}$, volunteers voted that nearly 20% of the generated heads look even more rational than the ground-truth heads, which verified that our model

| Attitude Matching | $D_{test}$ | $D_{ood}$ |
|-------------------|-----------|-----------|
| Positive          | 38.9 / 7.8| 48.2 / 21.9|
| Neutral           | 39.1 / 11.2| 49.7 / 17.0|
| Negative          | 40.7 / 14.1| 37.4 / 17.9|

Table 4. The mean and variance values of the accuracy about identifying the listeners’ attitude across all volunteers.
could generate responsive listeners consistent with subjective human perceptions. And surprisingly, our generated results in \( \mathcal{D}_{ood} \) were preferred by more volunteers.

Our second user-study results are shown in Table 4. Each volunteer was given 90 generated listening clips under three different attitudes. For each attitude, we calculate the mean accuracy and accuracy variance across all volunteers for analysis. The results show that both in \( \mathcal{D}_{test} \) and \( \mathcal{D}_{ood} \), our model is capable of generating listening head yielding to the required attitude. The mean accuracy in \( \mathcal{D}_{ood} \) shows that our model can capture the general listener patterns by attitude. While the larger accuracy variance in \( \mathcal{D}_{ood} \) indicates that there is still room for modeling attitudes.

Ablation studies and analysis We did ablation studies about the impact of different kinds of speaker signals for listening head modeling. The qualitative evaluation result is shown in Fig. 6. Here we set 6 frames as sampling interval to make a clear visualization. We can see that, compared to the Audio + Video based generations, the intensity of attitude generation significantly decrease (frames 24, 30) with the lack of audio inputs. And without speaker visual inputs, the generated listener loses focus, resulting in a lack of head motion controlling (frames 18, 24).

We also perform a user study to verify the sensitivity of human senses to the generated results. Given the randomly shuffled ground-truth speaker video with the generated listening heads based on different kinds of input signals, volunteers were asked to rank the listening head from the best one to worst one. We statistic the mean and variance occurrences of the “best” choice that appears in each listener in Table 5. The better results of Audio+Visual based generations reveal that humans are capable of distinguishing between good and bad listeners. The results of high mean value and low variance is also consistent with the common sense: only when we look and hear, can we act as better responsive listeners.

### 6. Conclusion

In this paper, we define the responsive listening head generation task. It aims to generate a responsive video clip for a listener with the understanding of the speaker’s facial signals and voices. Further, the high-quality responsive listener dataset (RLD) is contributed for addressing this problem. The responsive listener generation baseline can synthesis active listeners, which are more consistent with human perception. We expect that RLD could benefit the human-computer interaction research.

### Limitations

One potential limitation of our constructed dataset is that the attitude is assumed to be consistent across the clip, since we cut and annotate short clips from the candidate video. However, as shown in the qualitative results, the generated head sequences can vary from one common head respecting different attitudes. We may deduce that our model is feasible to the attitude-transferable conversations.

### 7. Applications and Ethical Impact

Active listening faces ineffective communication and plays an important role in human-to-human interaction. People are encouraged to learn to actively listen to others in many scenarios, such as doctor - patient, teacher - student, salesperson - customer, etc. Our proposed responsive listening head generation task fills a gap in modeling face-to-face communication in the computer vision area. It can be applied to many scenarios such as human-computer interaction, intelligence assistance, virtual human, etc. It would contribute to the mutual interaction between the virtual human and the real human. It can also be adopted to virtual audience modeling or providing guidance about how to act as an active listener.

The RLD dataset would be released only for research purposes under restricted licenses. The responsive listening patterns are identity-independent, which reduces the abuse of facial data. The only potential social harm is “fake content”, while different from talking head synthesis, responsive listening can hardly harm the information fidelity.
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A. Dataset Statistics

A.1. Clip Length / Duration Distribution

We counted the distribution of clip lengths and the corresponding duration percentage in RLD, and the results are shown in Fig. 7. Most of the clips are shorter than 10 seconds, while it only maintains 21% duration in our dataset. There also exist long clips (> 30 seconds), with 7% clips and 25% total duration in the dataset.

![Figure 7. The clip length distribution and the corresponding duration percentage in RLD dataset.](image)

A.2. Identities

The RLD dataset contains 97 identities. In the Fig. 9, we picked a random image for each identity. It can be found that there are different genders and races; thus, the potential ethics problems can be reduced, i.e., the dataset represent the diversity of the community.

![Figure 8. The identity distribution in our dataset.](image)

Some identities in our dataset may act as different roles (speaker/listener) and present different listener patterns under different attitudes. So, we statistic the identity distribution in Fig. 8. This demonstrates the diversity of our dataset.

B. IRB Approval

The YouTube community has a strict censorship mechanism to avoid violent or dangerous content [31]. And as shown in the copyright ¹, research purpose is considered fair use, which is allowed the reuse of copyright-protected material without getting permission from the copyright owner. This guarantees our dataset is congruence with the ethics guidelines.

¹https://www.youtube.com/howyoutubeworks/policies/copyright/#fair-use
Figure 9. Ninety-two identities with different genders and races in our dataset.