FillerSpeech: Towards Human-Like Text-to-Speech Synthesis with Filler Injection and Filler Style Control

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Abstract

Recent advancements in speech synthesis have significantly improved the audio quality and pronunciation of synthesized speech. To further advance toward human-like conversational speech synthesis, this paper presents FillerSpeech, a novel speech synthesis framework that enables natural filler insertion and control over filler style. To address this, we construct a filler-inclusive speech data, derived from the open-source large-scale speech corpus. This data includes fillers with pitch and duration information. For the generation and style control of natural fillers, we propose a method that tokenizes filler style and utilizes cross-attention with the input text. Furthermore, we introduce a large language model-based filler prediction method that enables natural insertion of fillers even when only text input is provided. The experimental results demonstrate that the constructed dataset is valid and that our proposed methods for filler style control and filler prediction are effective. Our code and demo are available at https://fillerspeech.github.io/main.

1 Introduction

Text-to-Speech (TTS) synthesis systems (Le et al., 2023; Li et al., 2024; Peng et al., 2024; Wang et al., 2025) have undergone remarkable advancements in recent years, particularly in achieving high-quality audio generation (Lee et al., 2025) and natural pronunciation (Ju et al., 2024). These improvements have paved the way for applications in various domains, such as virtual assistants, audiobooks, and human-computer interaction. Despite these advancements, achieving human-like conversational speech remains a challenging frontier.

Fillers, such as 'um', 'uh', or 'well', are an integral part of the natural human conversation (Zhu et al., 2022; Dinkar et al., 2022). They serve various functions, including signaling hesitation, buying time for thought formulation, or maintaining the flow of dialogue. When these elements are missing in synthesized speech, it can sound unnatural, making it less effective in applications that require natural human interaction.

In previous research, there have been attempts to address filler speech synthesis. (Éva Székely et al., 2019a) focused on training fillers as separate acoustic models to generate natural speech, while (Éva Székely et al., 2019b) learned fillers as tokens from a spontaneous conversational speech dataset. However, these models were limited to a narrow range of filler types such as 'uh' and 'um', which constrained their ability to handle diverse styles. (Yan et al., 2021) introduced an adaptive text-to-speech model to capture spontaneous speaking styles but did not explicitly focus on modeling fillers as non-verbal components of speech. (Fernandez et al., 2022) proposed a method to incorporate conversational style, including interjections, but struggled to naturally generate and control fillers seamlessly. (Wang et al., 2022) adopted a sampling-based approach for filler insertion but relied heavily on statistical methods, which often lacked coherence with the given textual context. These studies, while pioneering, revealed challenges in learning diverse filler styles and enabling precise text-based control for natural synthesis.

To tackle this challenge, we propose FillerSpeech, a novel framework for text-to-speech synthesis with filler injection and filler style control. We first construct a filler-inclusive speech dataset derived from the large-scale Libriheavy corpus (Kang et al., 2024) using our proposed method to label fillers with pitch and duration information, thereby eliminating the need for manual annotation. To achieve speech synthesis with controllable filler style, we employ tokenization of filler style and utilize cross-attention to effectively leverage word-level filler style tokens. Additionally, a pitch predictor is integrated into the text encoder to enhance the overall quality of the synthesized speech and

the control over filler styles. While filler selection can be performed manually, we additionally introduce a large language model (LLM)-based filler prediction method, allowing fillers to be naturally inserted based solely on input text. Experimental results validate the effectiveness of our method, demonstrating that FillerSpeech synthesizes natural and controllable speech, enhancing the realism of conversational speech applications.

2 Related Work

2.1 Flow Matching in Speech Synthesis

Flow matching has emerged as a powerful technique for speech synthesis, offering advantages in both quality and efficiency compared to traditional diffusion-based approaches (Popov et al., 2021; Kim et al., 2022).

Several recent works have explored the application of flow matching to various aspects of speech synthesis. (Velugoti et al., 2023) builds upon the flow-matching framework by introducing a rectified flow approach that improves synthesis efficiency while maintaining high-quality audio generation. (Le et al., 2023) further advances the field by adopting a versatile, non-autoregressive approach. It not only generates Mel-spectrograms but also supports speech inpainting and style transfer, showcasing robustness in both seen and unseen scenarios. (Kim et al., 2023) proposes a data-efficient zero-shot TTS method that leverages a speech-prompted text encoder combined with flow matching. (Mehta et al., 2024) leverages optimal-transport conditional flow matching to generate high-quality speech with only a few synthesis steps.

More recently, (Wu et al., 2024) takes flow-matching-based synthesis a step further by incorporating dynamic emotional control, enabling the generation of speech with time-varying emotional expressions. Similarly, (Kanda et al., 2024) focuses on fine-grained emotional control, specifically targeting laughter synthesis, offering a highly expressive and adaptable speech synthesis framework.

Flow matching can generate diverse and natural outputs while maintaining computational efficiency. By leveraging flow matching, we aim to address the challenges of generating expressive filler-inclusive speech, ensuring both high quality and controllability in filler generation.

2.2 Large Language Models

Large language models (LLMs) offer transformative advancements in understanding and generating human-like text. GPT-3 (Brown et al., 2020) and PaLM (Chowdhery et al., 2023) have demonstrated remarkable capabilities in zero-shot and few-shot learning, enabling them to excel in tasks ranging from text summarization to complex dialogue generation.

LLaMA (Touvron et al., 2023a) has gained significant attention as an open-source model designed to provide high-quality language understanding while being computationally efficient. Its lightweight architecture and pretraining on diverse datasets have made it a popular choice for researchers and practitioners. The LLaMA family of models balances performance and scalability, making it well-suited for applications in conversational AI, machine translation, and text-based creative generation. Building on the success of LLaMA, LLaMA 2 (Touvron et al., 2023b) introduced several enhancements, including improved training method, expanded datasets, and optimized architectures. These improvements have enabled LLaMA 2 to achieve superior performance across a broader range of tasks while maintaining computational efficiency.

Extending LLaMA's foundation, Vicuna (Chiang et al., 2023) focuses on enhancing conversational capabilities by fine-tuning on high-quality dialogue datasets. Vicuna-7B, in particular, optimizes LLaMA for interactive tasks, delivering context-aware and coherent responses. The recent Vicuna-7B further refines these conversational skills, excelling in dialogue-focused applications such as chatbots, virtual assistants, and customer support systems. We leverage the strengths of Vicuna-7B to enhance filler prediction in speech synthesis.

3 Dataset Construction

3.1 Filler-Inclusive Data Collection

To train FillerSpeech, we construct a dataset comprising speech samples that each contain at least one filler. Fillers can generally be categorized into lexical fillers (e.g., "like," "you know") and non-lexical fillers (e.g., "uh," "um"). In this work, we focus on non-lexical fillers, as they are more universally applicable and less dependent on linguistic context. Based on previous studies (Ward, 2006; Wang et al., 2022), we curate a list of common

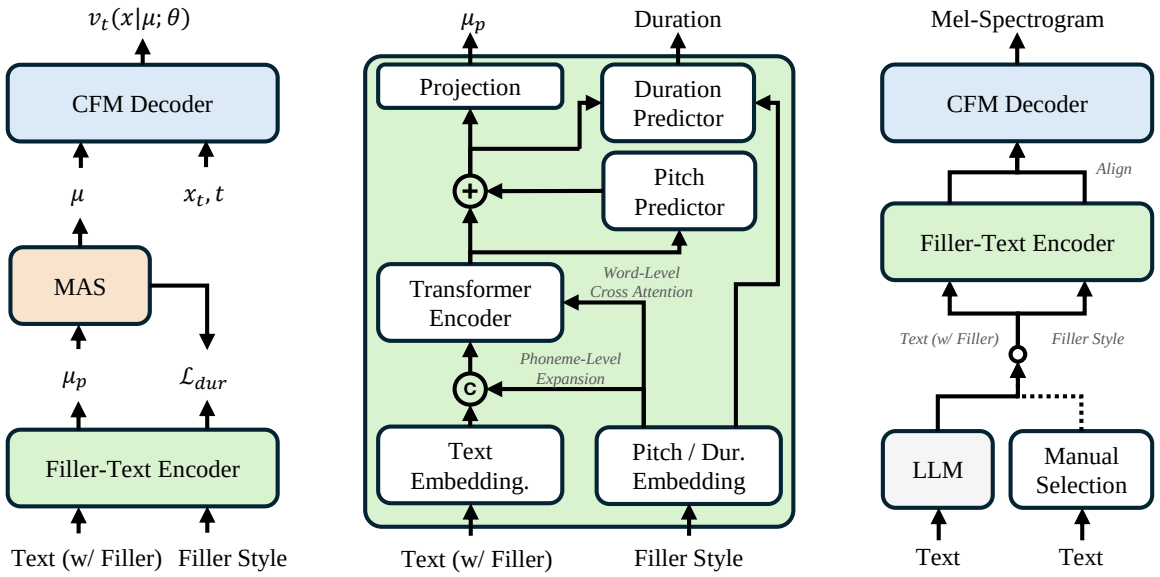


Figure 1: Overview of FillerSpeech. During inference, our approach leverages a fine-tuned LLM to predict filler attributes from the input text, or alternatively, users can manually select the desired filler details.

fillers: "ah", "aha", "eh", "ha", "hm", "huh", "oh", "uh", "um", "well", "yeah", "ya". Using a large-scale corpus of high-quality speech, we identify and extract speech samples that contain these fillers. This process enables us to build a comprehensive and diverse dataset tailored to the specific needs of filler-inclusive speech synthesis.

3.2 Style Labeling for Fillers

In addition to collecting filler-inclusive data, we also labeled the fillers with style information to facilitate controllable generation. The style labels focus on two key attributes: pitch (F0) and duration. To accurately identify the location of fillers within the audio samples, we first align the speech with its corresponding text using a external aligner. This alignment step provides precise segmentation of fillers, which is essential for subsequent style labeling.

For pitch labeling, we first extracted F0 values from the audio and then label each filler as high, medium, or low based on average pitch values. We compute these averages in two ways: one method calculates the average pitch for each filler type, and the other computes the average pitch of words within an utterance. Details are provided in Appendix E.1.

Since pitch characteristics differ significantly by gender, we labeled male and female speakers separately. To determine the pitch height, we used semitone differences as a threshold. Specifically, fillers were labeled as high or low if their pitch deviated by more than four semitones from the reference.

For duration labeling, we calculated the average duration of each filler type and categorized instances as long or short. Fillers in the top 25% of the duration distribution were labeled as long, while those in the bottom 25% were labeled as short. By considering both pitch and duration, the dataset captures the prosodic and temporal characteristics of fillers, offering detailed labels for precise control in filler synthesis.

4 Method

We present a speech synthesis method that inserts fillers and enables control over their style. Our model leverages filler style tokens in conjunction with a pitch predictor and cross-attention to modulate speech style. In addition to directly manipulating filler style, we propose a fine-tuning approach for LLMs to predict styled fillers, thereby enabling the synthesis of filler-inclusive speech from text alone. Detailed descriptions of each component are provided in the following subsections.

4.1 Tokenization of Filler

To effectively incorporate fillers into speech synthesis, we adopt a phoneme-based tokenization approach for fillers rather than tokenizing each filler as a whole. This is because fillers are generally fewer in number compared to phonemes, and they are ultimately composed of phonemes. Consequently, fillers undergo the same phoneme

conversion process as other text elements. This tokenization approach ensures that fillers and regular words blend naturally into synthesized speech.

For filler style, we tokenize pitch and duration using discrete labels. Regular words, which lack pitch and duration labels, are assigned null labels. Since pitch is strongly correlated with speaker gender, we further tokenize pitch labels based on gender.

4.2 Filler Style Control

To condition the encoder on pitch of filler at the phoneme level, the pitch tokens are first embedded, then expanded to match the phoneme-level resolution, and finally concatenated with the phoneme embeddings of the text. To further enhance the integration of fillers into synthesized speech, the encoder computes cross-attention between phoneme-level text representations and word-level pitch embeddings.

For duration control, the duration tokens are first embedded and then used together with the text representations as input to the duration predictor.

To control filler styles more precisely, we explicitly include pitch information in training. A pitch predictor estimates appropriate pitch values from the text representation. By explicitly modeling pitch during training, the text encoder learns to better capture the prosodic characteristics necessary for natural filler generation and style control.

4.3 Prior Loss for Filler Representation

We compute a prior loss between the encoder outputs and the target Mel-spectrograms. Unlike conventional methods (Popov et al., 2021; Mehta et al., 2024) that compute prior loss on a sampled subset of encoder outputs to improve training efficiency, we compute the loss for all encoder outputs. This is because fillers constitute a small fraction of the text, making it more likely that the sampling process will primarily learn segments without fillers. Since style tokens appear only in segments containing fillers, the controllability of filler style is consequently diminished. After computing the prior loss, we follow standard practices by sampling a subset of encoder outputs for the decoder input to improve training efficiency.

4.4 Flow Matching Decoder

Our decoder is built on the flow matching framework, a generative diffusion model that employs optimal transport conditional flow matching (OT-CFM) for efficient and probabilistic data transformation. The flow matching process models a probability path that connects a simple prior distribution p_0 (e.g., Gaussian noise) to a complex data distribution $q(x)$, (e.g., Mel-spectrogram). This is achieved by defining a vector field $\boldsymbol{v_t(x)}$ that governs the transformation of samples over time t through an ODE as follows:

$$\frac{d}{dt}\phi_t(x) = \boldsymbol{v}_t(\phi_t(\boldsymbol{x})); \qquad \phi_0(\boldsymbol{x}) = \boldsymbol{x}. \quad (1)$$

Here, $\phi_t(x)$ represents the trajectory of a sample from the prior distribution to the target distribution. In OT-CFM, the training objective minimizes the difference between the predicted vector field $\boldsymbol{v_t(x)}$ and the ideal vector field $\boldsymbol{u_t(x)}$ as follows:

$$\mathcal{L}(\theta) = \mathbb{E}_{t,x_0,x_1}\|\boldsymbol{u}_t^{\mathrm{OT}}(\phi_t^{\mathrm{OT}}(\boldsymbol{x})|\boldsymbol{x}_1) - \boldsymbol{v}_t(\phi_t^{\mathrm{OT}}(\boldsymbol{x})|\boldsymbol{\mu};\theta)\|^2. \quad (2)$$

This formulation ensures that the decoder learns an efficient and smooth transformation from latent noise to Mel-spectrograms. The simplicity of the vector field $\boldsymbol{u_t(x)}$, which changes linearly along the trajectory, reduces the number of required synthesis steps compared to traditional diffusion models, significantly improving speed and accuracy.

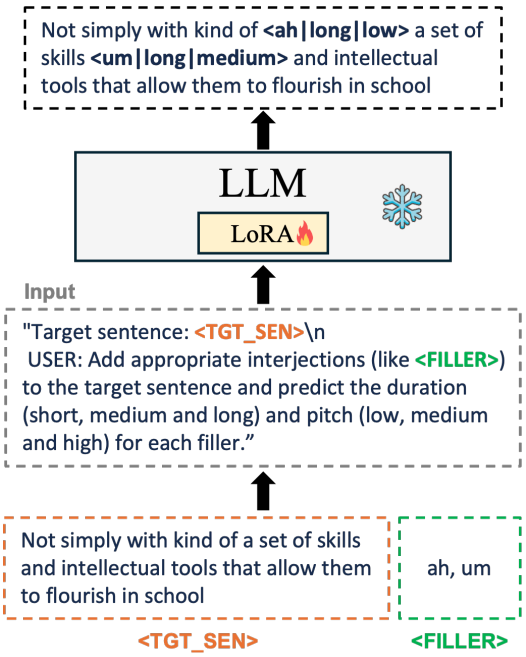


Figure 2: Overview of the fine-tuning LoRA for the filler prediction.

4.5 LLM-based Filler Prediction

To insert fillers naturally based on the input text, we propose an LLM-based filler prediction method. To leverage the reasoning capabilities of LLMs

(Wei et al., 2022) while mitigating catastrophic forgetting, we fine-tune the LLM using a Low-Rank Adaptation (LoRA) adapter (Hu et al., 2022). Our method involves predicting both the position and type of fillers in the input text. Simultaneously, we predict the appropriate duration and pitch for each filler, considering the surrounding context within the input text.

To enable the model to perform a variety of filler prediction tasks with a single model, we created instruction prompts that allow for different levels of specification. These prompts include scenarios where the filler type is specified, the filler type and position are given, a set of potential fillers is provided, or only the filler position is specified, allowing the model to predict the remaining characteristics such as duration, pitch, and type.

The LLM is trained separately from the TTS model, and during the speech synthesis inference process, LLM filler prediction can be utilized as needed. Detailed information on the prompt is provided in Appendix C.

5 Experiments

5.1 Dataset

Using the method described in Section 3, we constructed a filler-inclusive speech dataset based on the large-scale Libriheavy corpus, which comprises 50,000 hours of speech data. The resulting dataset comprises 4,460 speakers and a total of 2,116 hours of speech data. Each sentence contains at least one filler, with each filler containing pitch and duration information. For the validation and test sets, we selected 50 speakers and obtained 2,707 and 2,966 sentences, respectively.

5.2 Implementation Details

5.2.1 Data Construction

For constructing the filler-inclusive dataset, we employed the Montreal Forced Aligner (MFA) (McAuliffe et al., 2017) as the external aligner and Parselmouth (Jadoul et al., 2018) as the pitch extractor.

5.2.2 Speech Synthesis

The flow matching decoder in our model was implemented using a Transformer-based U-Net architecture, ensuring efficient and high-quality Mel-spectrogram generation. For speaker information extraction, we employed the style encoder from Meta-StyleSpeech model (Min et al., 2021). We integrated the pitch predictor into our framework to achieve accurate and controllable style generation, adopting the structure proposed in (Ren et al., 2021). To compute the alignment between the encoder output and Mel-spectrogram, we employed super monotonic alignment search (Lee and Kim, 2024). For training, we used two NVIDIA RTX A6000 GPUs, with a batch size of 32 per GPU. The model was trained for one million steps, which took 83 hours. The overall parameter count of our model is 60.11M, and additional details regarding the hyperparameters are provided in Table 6. As the vocoder, we used BigVGAN (gil Lee et al., 2023) for waveform generation.

5.3 LLM-based Filler Prediction

We employed Vicuna-7B (Chiang et al., 2023) as our LLM model for fine-tuning on the filler prediction task using a LoRA adapter. Additionally, to validate the performance of the baseline LLM used for the prompt-based filler prediction task, we froze various instruction-tuned LLMs from the LLaMA (Touvron et al., 2023a) and Qwen (Yang et al., 2024) families and fine-tuned them on the filler prediction task using a LoRA adapter. Their performance is compared in Table 3. In particular, Vicuna w/ sampling-based filler insertion (SFI) (Wang et al., 2022) was fine-tuned by adding an additional output branch to Vicuna-7B, following the approach of SFI , with the LoRA adapter integrated during fine-tuning. This branch consists of a single 13-way softmax prediction layer that estimates the probability of 13 filler words, as well as the probability of no filler insertion.

5.4 Evaluation Metrics

5.4.1 Speech Synthesis

We evaluated the performance of the synthesized speech using both subjective and objective metrics. To evaluate the naturalness of the synthesized speech and the similarity to the target speaker, we conducted a mean opinion score (MOS) test and a similarity mean opinion score (sMOS) test. In the MOS test, evaluators rated the naturalness of the speech on a 5-point scale (1 to 5), while in the sMOS test, they assessed how similar the synthesized speech was to the target speech on the same scale. We employed the UTMOS (Saeki et al., 2022) model to automatically predict MOS scores, providing an objective measure of speech quality. To evaluate the pronunciation accuracy of synthesized speech, we used automatic speech

Table 1: Experimental results of the proposed method. Con, PP, and CA indicate style controllability, pitch predictor, and cross attention, respectively. The results for both MOS and sMOS are reported with a 95% confidence interval.

Method	Con	Token	PP	CA	MOS (↑)	sMOS (↑)	UTMOS (↑)	WER (↓)	PER (↓)	SECS (↑)
GT	-	-	-	-	4.02 ± 0.05	4.22 ± 0.05	3.6038	5.64	14.27	0.8809
Vocoded	-	-	-	-	3.99 ± 0.05	4.16 ± 0.05	3.4116	5.64	14.48	0.8814
Matcha-TTS	✗	✗	✗	✗	3.62 ± 0.07	3.47 ± 0.07	3.3536	**4.56**	11.11	0.7723
FillerSpeech	✓	✓	✗	✗	3.21 ± 0.07	3.39 ± 0.07	3.2020	4.60	**11.05**	0.7698
	✓	✓	✓	✗	3.80 ± 0.06	$\mathbf{3.53} \pm 0.07$	3.8307	9.36	14.28	0.7693
	✓	✓	✓	✓	$\mathbf{3.84} \pm 0.06$	3.50 ± 0.07	**3.8780**	6.33	12.10	**0.7736**

recognition (ASR) models, specifically Whisper (Radford et al., 2023) and Wav2Vec 2.0 (Baevski et al., 2020), to calculate word error rate (WER), and phoneme error rate (PER). To verify how well the synthesized speech matched the target speaker's voice, we extracted speaker embeddings using Resemblyzer[1] and computed speaker embedding cosine similarity (SECS).

5.4.2 Filler Prediction

To evaluate the performance of the language model's filler prediction, we calculate the accuracy of filler position, type, duration, and pitch by comparing the model's outputs to the ground truth, with results reported as percentages. This evaluation measures the degree of agreement between the predicted and ground truth labels for each aspect. Note that the accuracy for filler type, duration, and pitch is computed only for those instances where the predicted filler is inserted at the correct position as specified in the ground truth.

In addition to quantitative accuracy, qualitative evaluation is conducted using GPT-4o (OpenAI, 2024), which assigns scores to the model's performance in two filler prediction tasks: position (Score-P) and type (Score-T). Scores range from one to five, where a score of one indicates poor performance and a score of five indicates excellent performance. Given the inherent variability of natural speech, multiple filler placements may appear natural within a sentence. Therefore, qualitative evaluation is crucial to capture these nuances, which is why we leverage GPT-4o for this assessment.

Filler position evaluation assesses how appropriately the model places fillers within sentences, focusing on the naturalness and suitability of their placement. Filler type evaluation measures the appropriateness of the specific filler words predicted by the model, ensuring that they align with the context of the sentence.

The scoring process for all tasks takes into account factors such as naturalness, contextual relevance, fluency, and overall suitability for speech interaction, providing a comprehensive assessment of the model's performance. For more details on the evaluation process, please refer to Appendix D.3.

6 Results

6.1 Speech Synthesis with Filler Injection

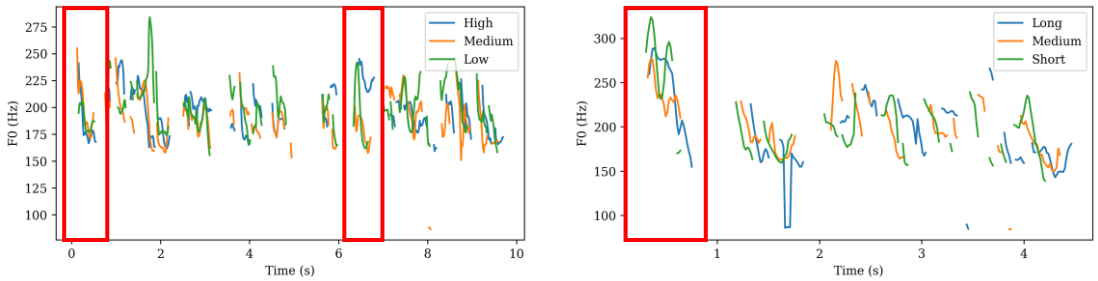
Table 1 shows the results of subjective and objective evaluations. The proposed method successfully synthesizes speech with natural and contextually appropriate filler injection. Through both subjective MOS test and objective metrics such as UTMOS and SECS, the synthesized speech demonstrated high naturalness, even with fillers inserted into various positions in the text.

Notably, the inclusion of pitch information led to significant improvement in UTMOS, indicating enhanced speech naturalness. However, a decline in pronunciation accuracy was observed, as reflected in increased WER and PER values. This suggests that incorporating pitch information into the prior loss computation may cause the text encoder to focus more on acoustic features rather than text-based representations. Consequently, this shift could negatively impact the encoder's ability to accurately represent phonetic information, leading to reduced pronunciation accuracy. Nevertheless, by incorporating cross-attention, we were able to improve both pronunciation accuracy and speaker similarity.

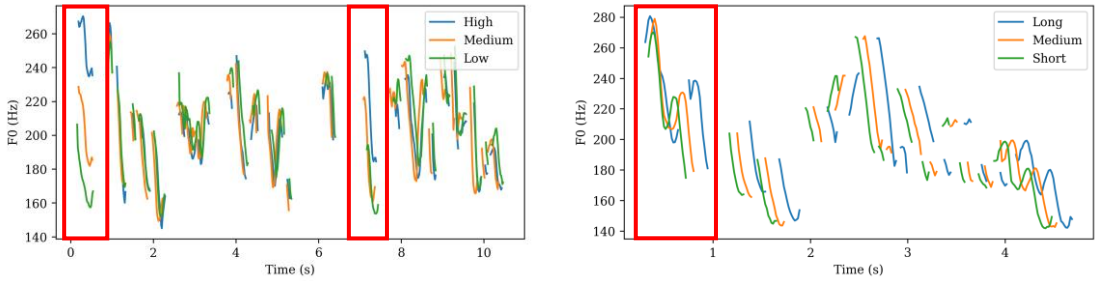
6.2 Filler Style Control

Our method provides precise control over filler styles, allowing the pitch and duration of fillers to be modulated as desired. To validate this capability, we conducted experiments using the same text,

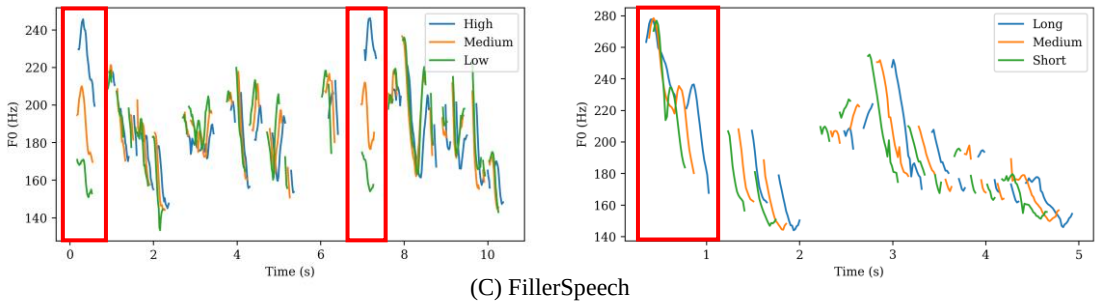
[1] https://github.com/resemble-ai/Resemblyzer



(a) FillerSpeech without pitch predictor and cross attention



(b) FillerSpeech without cross attention



(C) FillerSpeech

Figure 3: Pitch track visualization of synthesized speech with different filler styles. The red boxes highlight regions where filler words occur. The left column shows pitch control, while the right column shows duration control.

where the same filler was synthesized under different style conditions. Figure 3 presents pitch track plots, showing that the generated pitch contours change according to the specified style tokens. For example, when a higher pitch style was applied, the filler's pitch consistently increased compared to other conditions, demonstrating the method's robustness in controlling prosodic attributes. This highlights the model's ability to adapt fillers dynamically based on stylistic requirements, a critical feature for expressive and context-aware speech synthesis.

Comparisons between FillerSpeech and models with removed modules reveal that both the pitch predictor and cross-attention significantly affect the filler's pitch control capabilities. Notably, while the pitch predictor slightly degrades pronunciation accuracy, it markedly improves control over the filler's pitch. Similarly, cross-attention, by incorporating word-level pitch conditions, adds stability to the control. In contrast, duration control remains largely unchanged, indicating that pitch information does not substantially contribute to predicting duration.

6.3 LLM-based Filler Prediction

Table 2 shows that our proposed method outperforms the baseline models in filler prediction. Specifically, the Vicuna w/o FT model fails to predict fillers accurately. Although the Vicuna w/ SFI model predicts only position and type, its performance is significantly inferior to that of our model.

To verify that the Vicuna-7B model was the optimal choice for the LLM component, we compared its performance with that of other instruction-tuned LLMs. All models were trained under identical conditions, with only the LLM component varied. The results are presented in Table 2. Vicuna-7B, fine-tuned on dialogues between GPT and humans, outperforms other models.

6.3.1 Accuracy Evaluation

For filler position accuracy, the model achieved a high score of 82.56, indicating strong precision in placing fillers correctly within sentences. This

suggests that the model is effective at maintaining the natural flow of the sentence, which is crucial for realistic filler insertion in spontaneous speech.

In terms of filler duration, the accuracy was 52.46. This reflects the difficulty of predicting the appropriate duration for filler pauses, as their natural length can vary significantly depending on the context. Filler durations in spontaneous speech are flexible, influenced by factors such as hesitation, emphasis, and speaker intent. This variability points to the need for further refinement of the model to better capture these nuances, which are vital for replicating natural speech patterns.

For filler pitch accuracy, the model scored 63.27, indicating moderate performance. While this score is reasonable, it reveals that predicting pitch for fillers is still a challenging task. The gap between the model's performance on pitch and position accuracy suggests that there is room for improvement, particularly in understanding and predicting prosody, which is an essential component for natural-sounding filler usage.

6.3.2 LLM-based Evaluation

For filler position, the model achieved a score of 3.31, very close to the ground truth (GT) score of 3.25. This minor discrepancy suggests that the model is almost as accurate as the ground truth when it comes to determining the appropriate position of fillers, with only a slight difference in the evaluation.

In terms of filler type, the model scored 3.27, slightly lower than the GT score of 3.30. This result indicates that the model generally predicts appropriate and natural filler types for the given context, with only a small deviation from the expected outcome.

Overall, the model demonstrated strong performance across all tasks, particularly excelling in predicting filler positions. Although its accuracy for filler duration was slightly lower and there is still room for improvement in pitch prediction, the qualitative evaluation through GPT scores showed that the model predictions were very close to the ground truth. In fact, for filler duration and pitch, the model even outperformed the ground truth. These results highlight the effectiveness of the model in predicting filler characteristics while also identifying areas for further refinement, especially in filler timing and pitch.

Table 2: Comparison of filler prediction performance. Vicuna w/ SFI model only supports position and type prediction.

Method	Accuracy				GPT Scores	
	Position	Type	Duration	Pitch	Position	Type
GT	-	-	-	-	3.25	3.30
Vicuna w/o FT	1.35	13.33	46.67	24.44	2.44	2.47
Vicuna w/ SFI	59.67	38.14	-	-	2.41	2.81
Vicuna w/ LoRA	**82.56**	**78.44**	**52.46**	**63.27**	**3.31**	**3.27**

Table 3: Comparison of LoRA-based fine-tuning results for filler prediction across instruction-tuned LLMs.

Method	Accuracy				GPT Scores	
	Position	Type	Duration	Pitch	Position	Type
GT	-	-	-	-	3.25	3.30
Qwen-1.5B	69.65	60.15	49.87	61.95	3.10	3.13
Qwen-3B	73.59	57.66	49.03	61.19	3.23	3.14
Qwen-7B	75.20	59.76	51.43	62.02	3.23	3.19
LLaMA-1B	81.11	72.85	**52.54**	62.36	3.25	3.22
LLaMA-3B	80.13	73.78	50.28	62.68	3.27	3.20
LLaMA-8B	81.65	76.43	50.55	**63.71**	3.29	3.22
Vicuna-7B	**82.56**	**78.44**	52.46	63.27	**3.31**	**3.27**

7 Conclusion

In this paper, we introduced FillerSpeech, a novel speech synthesis framework that integrates filler insertion with style control. We constructed a filler-inclusive speech dataset from the large-scale speech corpus, leveraging an automated method to label fillers with pitch and duration information, thereby eliminating the need for manual annotation. Our approach employs cross-attention mechanisms and a pitch predictor to condition the model on filler style, which enhances the control over pitch. While fillers can be manually adjusted to achieve a desired style, we further propose an LLM-based filler prediction method that enables natural filler insertion based solely on text input. Experimental results demonstrate that cross-attention mechanisms and pitch predictor substantially improve both speech quality and style control, and the LLM-based filler prediction method effectively predicts filler attributes from text.

8 Limitations

Our model is trained using three discrete labels for both pitch and duration. While this approach allows for effective control within the predefined label space, it limits the model's capability to achieve extreme or fine-grained control. In future work, we aim to explore more expressive speech synthesis and investigate control methods based on continuous values rather than categorical labels.

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Table 4: Inference performance of the CFM decoder with pitch predictor.

# Steps	RTF (↓)	UTMOS (↑)	WER (↓)	SECS (↑)
1	**0.0206**	3.7519	6.41	0.7507
2	0.0213	**3.8945**	**5.59**	0.7600
4	0.0227	3.8780	6.33	0.7736
8	0.0259	3.8260	7.03	**0.7779**

Table 5: Inference performance of the CFM decoder without pitch predictor.

# Steps	RTF (↓)	UTMOS (↑)	WER (↓)	SECS (↑)
1	**0.0201**	2.0691	**0.0356**	0.6925
2	0.0210	2.6805	0.0366	0.7323
4	0.0224	3.0658	0.0418	0.7578
8	0.0255	**3.2020**	0.0460	**0.7698**

A Analysis on Sampling Steps

In our analysis of the CFM decoder during inference, we evaluated the effect of varying the number of sampling steps by measuring the real time factor (RTF), UTMOS, WER, and SECS. As shown in Tables 4 and 5, our model achieves rapid performance improvements even with fewer sampling steps. This improvement is attributed to the use of a pitch predictor, which enables the decoder to condition on encoder outputs that include pitch information. Conversely, as the number of sampling steps increases, we observed a decline in UTMOS and WER, indicating that the pitch information employed for enhanced pitch style control does not necessarily improve pronunciation accuracy. Moreover, with additional sampling steps, SECS increases. This can be explained by the fact that our model's encoder outputs combine text, filler pitch style, and speaker representations, thereby reducing the relative influence of speaker information. Since the sampling process further conditions on the speaker information with encoder outputs, speaker similarity improves with more sampling iterations.

B Discussion

B.1 General Word Style Control

Due to our model's design which applies style conditioning at the positions of designated tokens, it is capable of modulating the style not only of these tokens but also of general words. Consequently, we demonstrate that even when only a subset of words in the speech data contains pitch or duration information, our approach enables fine-grained control over the overall speech style.

Table 6: Hyperparameters of FillerSpeech.

Module	Hyperparameter	FillerSpeech
Embedding	Text	192
	Speaker	64
	Pitch	64
	Duration	64
Encoder	Prenet Conv. Hidden Dim.	192
	Prenet Conv. Layers	3
	Prenet Conv. Kernel Size	5
	Prenet Dropout	0.5
	Transformer Hidden Dim.	320
	Transformer FFN Filter Channels	768
	Transformer Layers	6
	Transformer Kernel Size	3
	Transformer Attention Heads	2
	Transformer Dropout	0.1
	Projection Hidden Dim.	320
	Projection Layers	2
	Projection Kernel Size	3
	Projection Dropout	0.5
Pitch predictor	Conv. Hidden Dim.	192
	Conv. Layers	5
	Conv. Kernel Size	5
	Conv. Dropout	0.5
Duration predictor	Conv. Hidden Dim.	384
	Conv. Layers	2
	Conv. Kernel Size	3
	Conv. Dropout	0.1
CFM decoder	Channels	[512, 512]
	Dropout	0.05
	Blocks	1
	Mid Blocks	2
	Attention Heads	2
	Activation	snakebeta
	Solver	euler
	Sigma min	1e-4
Optimizer	Optimizer	Adam
	Learning Rate	0.0001
	Beta	[0.9, 0.98]

B.2 Potential Risks

While the advancements in speech synthesis technology offer significant benefits, they also raise concerns about potential malicious uses. The ability to generate highly realistic synthesized speech can be exploited to produce deceptive content, such as deepfakes or misleading information, which may have harmful societal implications. To address these risks, a discussion on synthesized speech detection and watermarking techniques during synthesis is necessary to authenticate and trace speech outputs.

B.3 AI asist

We used GPT-4o for proofreading, including typo and sentence correction.

C Prompt for Filler Prediction

To train our LLM to predict the appropriate position, type, duration, and pitch of fillers, as shown in Figure 4, we employed four different types of prompts.

In the first prompt type, the desired filler type is explicitly specified for prediction. In this case, **<TGT_SEN>** denotes the sentence into which the filler will be inserted, and **<FILLER>** indicates the desired filler type.

The second prompt type involves specifying both the desired filler type and the insertion position within the sentence. Here, **<TGT_SEN>** represents the sentence for filler insertion, **<FILLER>** stands for the desired filler type, and **<TGT_POS>** indicates the token position within **<TGT_SEN>** where the filler should be inserted.

For the third prompt type, a set of filler type options is provided, and the LLM selects the most appropriate filler from these options to insert into **<TGT_SEN>**.

In the fourth prompt type, similar to the third, a set of filler type options is given. However, in this case, the LLM not only selects the appropriate filler but also inserts it at the specified token position **<TGT_POS>** within **<TGT_SEN>**.

Across all prompt types, the predicted duration for each filler is classified as either short, medium, or long, while the predicted pitch is categorized as low, medium, or high.

D Details of Evaluation Metrics

D.1 Mean Opinion Score Test

For the subjective evaluation, we conducted both MOS and sMOS tests using Amazon Mechanical Turk, recruiting 20 evaluators for each test. For the evaluations, 50 utterances were randomly sampled from the test set. Additionally, we interspersed fake samples among the test utterances. We filtered out ratings from workers who gave scores to fake samples to exclude unreliable participants.

D.2 Automatic Speech Recognition for Filler-inclusive Speech

In typical TTS tasks, ASR used for pronunciation evaluation employs a text normalization process that includes the removal of filler words from the ASR output. However, because our approach intentionally synthesizes speech with fillers, we deliberately bypass the removal of filler words during text normalization. This allows us to directly assess the performance of our system in generating filler-inclusive speech.

D.3 GPT Score

Building on the studies (Chiang and Lee, 2023; Chiang et al., 2023; Zheng et al., 2023; Fang et al., 2025) that use LLM models to evaluate model outputs, we employ GPT-4o (OpenAI, 2024) to assess the filler prediction ability of our fine-tuned LLM. In this evaluation, GPT-4o examines two key aspects: the prediction of filler positions and the prediction of filler types.

For the filler position, GPT-4o assigns a score ranging from 1 to 5, where a higher score indicates better performance (1: Poor, 2: Below Average, 3: Neutral, 4: Good, 5: Excellent). The evaluation of filler types is carried out in the same manner, with GPT-4o using the identical 1 to 5 scoring scale. Detailed information on the evaluation prompt can be found in Figure 5. Here, the term **{sentence}** refers to the sentence into which the predicted filler is inserted.

E Analysis on Constructed Data

E.1 Comparison between Pitch labeling Method

We employ two complementary strategies for annotating filler pitch, each designed to capture different aspects of prosodic variation. First, we extract F0 values using Parselmouth and identify filler regions with the MFA. Based on these boundaries, we compute two sets of average F0 values: one for the filler segments and one for the entire utterance.

Our first labeling strategy focuses on comparing F0 values across fillers, independent of their utterance context. For each filler type, we calculate the median F0 separately for male and female speakers to reduce the impact of outliers and account for gender-specific pitch differences. We use XLSR-52-based gender recognition model[2]. Each filler instance is then labeled as low, medium, or high based on whether its F0 is at least four semitones below or above the gender-specific median. The threshold is defined as:

$$\text{threshold}_{\pm} = \text{median} \times 2^{\pm \frac{4}{12}}. \quad (3)$$

The second strategy normalizes filler pitch relative to the overall utterance. Here, we compare the F0 of filler regions to the average F0 of the entire sentence. Fillers whose F0 deviates by at least four semitones from the utterance average are labeled as low or high. If the proportion of fillers labeled as low or high is below 15% when using a four-semitone threshold, a three-semitone threshold is applied instead. As with the first method, these calculations are performed separately for male and female speakers to accommodate gender-specific pitch characteristics. The F0 ratio is computed as:

$$\text{F0 ratio} = \frac{\text{F0\_mean}}{\text{sentence\_F0\_mean}}, \quad (4)$$

with the threshold given by:

$$\text{threshold}_{\pm} = 2^{\pm \frac{4}{12}}. \quad (5)$$

These two methods provide complementary perspectives on pitch variation: one capturing filler-specific deviations across speakers and the other contextualizing filler pitch within each utterance. We evaluated both labeling strategies in our experiments and, as shown in Table 7, found that the first method yields superior performance in speech synthesis.

Table 7: Performance comparison of pitch labeling strategies.

Method	UTMOS (↑)	WER (↓)	SECS (↑)
First Strategy	**3.8780**	**6.33**	**0.7736**
Second Strategy	3.8240	7.55	0.7631

Figure 6 shows the F0 distributions for fillers computed using the first strategy. For most filler types, the distribution near the median is skewed toward values below the median. However, in general, the proportion of fillers labeled as high tends to be higher than those labeled as low.

[2] https://huggingface.co/alefiury/wav2vec2-large-xlsr-53-gender-recognition-librispeech

Type 1: Prompt template for filler prediction

Target sentence: **<TGT_SEN>**
USER: Add the specified fillers (like **<FILLER>**) to the target sentence to make it sound more natural. For each filler, also specify its duration (short, medium, long) and pitch (low, medium, high) that sound contextually appropriate and natural.
ASSISTANT:

Type 2: Prompt template for filler prediction

Target sentence: **<TGT_SEN>**
USER: Add the specified fillers (like **<FILLER>**) at target positions **<TGT_POS>** in the target sentence. For each filler, also specify its duration (short, medium, long) and pitch (low, medium, high) that sound contextually appropriate and natural.
ASSISTANT:

Type 3: Prompt template for filler prediction

Target sentence**: <TGT_SEN>**
Filler word options: oh, ah, ha, eh, aha, huh, hm, uh, yeah, mm, um, ya, well
USER: Add contextually appropriate fillers to the target sentence. For each filler, also specify its duration (short, medium, long) and pitch (low, medium, high) that sound contextually appropriate and natural."
ASSISTANT:

Type 4: Prompt template for filler prediction

Target sentence: **<TGT_SEN>**
Filler word options: oh, ah, ha, eh, aha, huh, hm, uh, yeah, mm, um, ya, well
USER: Add contextually appropriate fillers at target positions **<TGT_POS>** in the target sentence. For each filler, also specify its duration (short, medium, long) and pitch (low, medium, high) that sound contextually appropriate and natural."
ASSISTANT:

Figure 4: Sample templates for filler prediction (Type 1, 2, 3, 4)

Prompt for GPT Scores – Filler Position (Model: GPT-4o)

You are an expert evaluator of filler placement.
I need your help to evaluate the performance of a model in a filler prediction scenario.
The model receives a target sentence and generates a response by inserting fillers at specific positions.
Your task is to rate the model's response based only on the correctness of filler positions.
Ignore the content of the fillers themselves and focus strictly on whether **the placement of the fillers** aligns with natural speaking patterns.

Scoring Guidelines (Evaluate only the filler position!)
Provide a **single score** on a scale from **1 to 5**, where:

- **1**: Poor
- Fillers are placed incorrectly, disrupting the sentence's natural flow.
- **2**: Below Average
- Some fillers are misplaced, causing minor disruptions.
- **3**: Neutral
- Fillers are placed in acceptable locations but do not necessarily enhance the sentence.
- **4**: Good
- Fillers are mostly well-placed, making the sentence sound natural.
- **5**: Excellent
- Fillers are placed **perfectly**, improving the conversational tone.

Important: Focus **only** on **filler position** for this evaluation.

After evaluating, output the score **only as a number** (e.g., `4`).
Evaluate the following sentence:\n'**{sentence}**'

Prompt for GPT Scores – Filler Type (Model: GPT-4o)

You are an expert evaluator of filler types in natural speech.
I need your help to evaluate the performance of a model in a filler prediction scenario.
The model receives a target sentence and generates a response by inserting fillers of specific types at particular positions.

Your task is to rate the model's response based only on the naturalness and appropriateness of the filler types used in the sentence.
Consider the following aspects:

1. **Contextual Suitability**: Assess whether the chosen filler types (e.g., "um," "oh," "yeah") fit naturally within the conversational context of the sentence, enhancing the flow and coherence.
2. **Human-like Selection**: Determine if the filler type corresponds to what a human speaker would likely use in the given situation, considering the tone, intent, and conversational style of the sentence.

Scoring Guidelines
Provide a **single score** on a scale from **1 to 5**, where:

- **1**: Poor
- Filler types are unnatural or disrupt the conversational flow.
- **2**: Below Average
- Some filler types seem out of place or could be improved.
- **3**: Neutral
- Filler types are acceptable but do not necessarily enhance the sentence.
- **4**: Good
- Fillers are mostly well-chosen, making the sentence sound natural.
- **5**: Excellent
- Filler types are **perfectly suited**, improving the conversational tone.

Important: Focus **only** on the filler type selection, not the placement.
Ignore grammar, word choice, and meaning—evaluate only whether the **type of fillers** used is what a human would naturally say.
After evaluating, output the score **only as a number** (e.g., `4`).
Evaluate the following sentence:\n'**{sentence}**'

Figure 5: Prompt templates for GPT-based filler evaluation, using a 1–5 scoring scale.

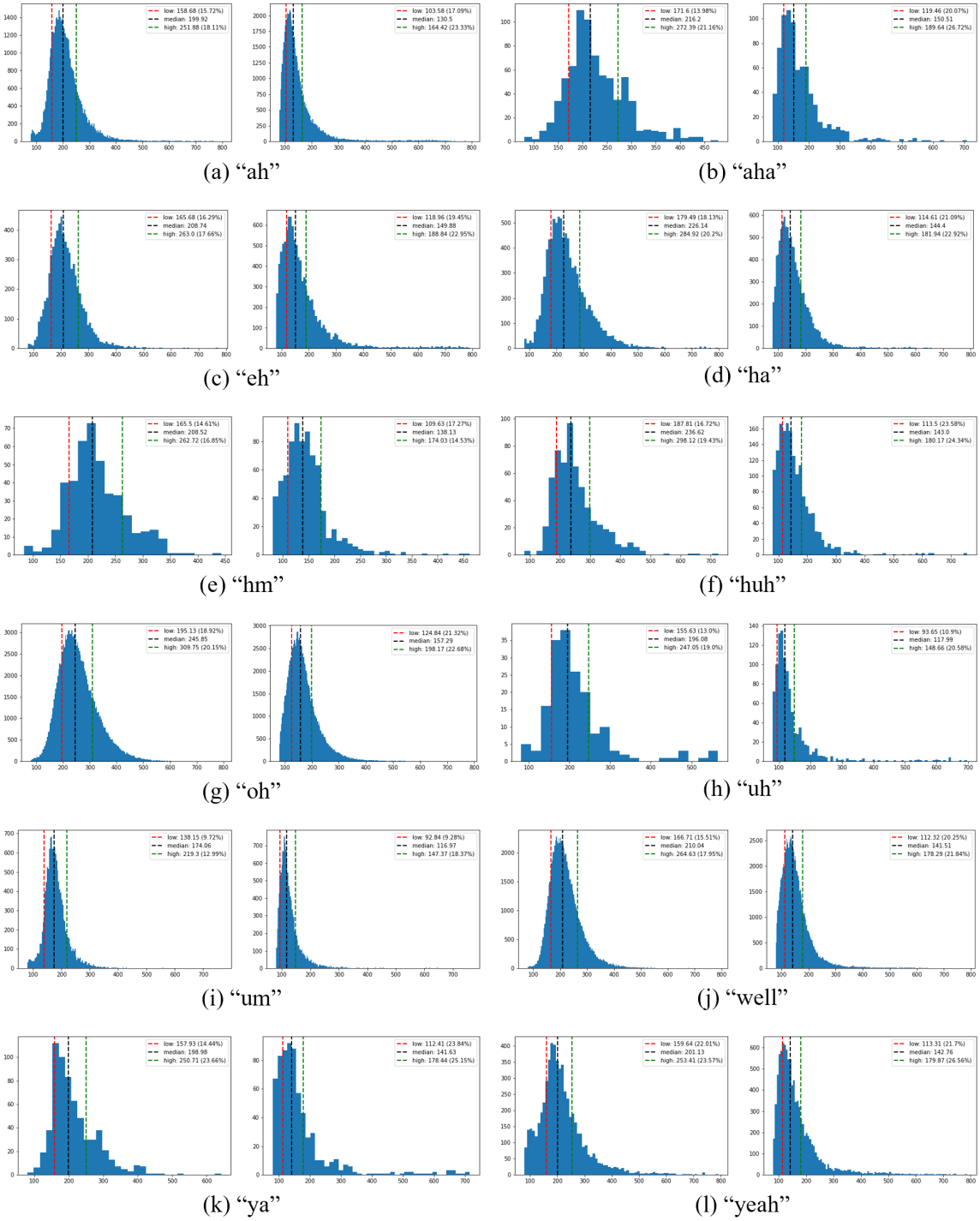

Figure 6: F0 distribution for each filler type. Odd-numbered columns correspond to female speakers, while even-numbered columns correspond to male speakers.

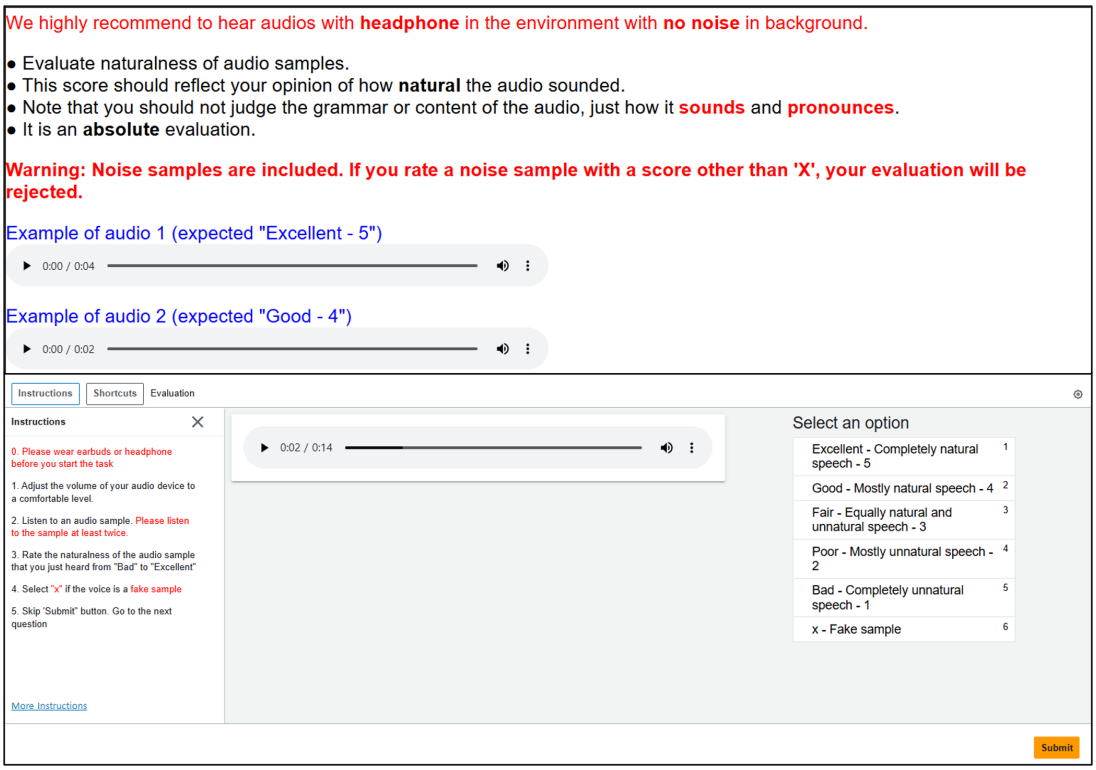

Figure 7: MOS evaluation interface.

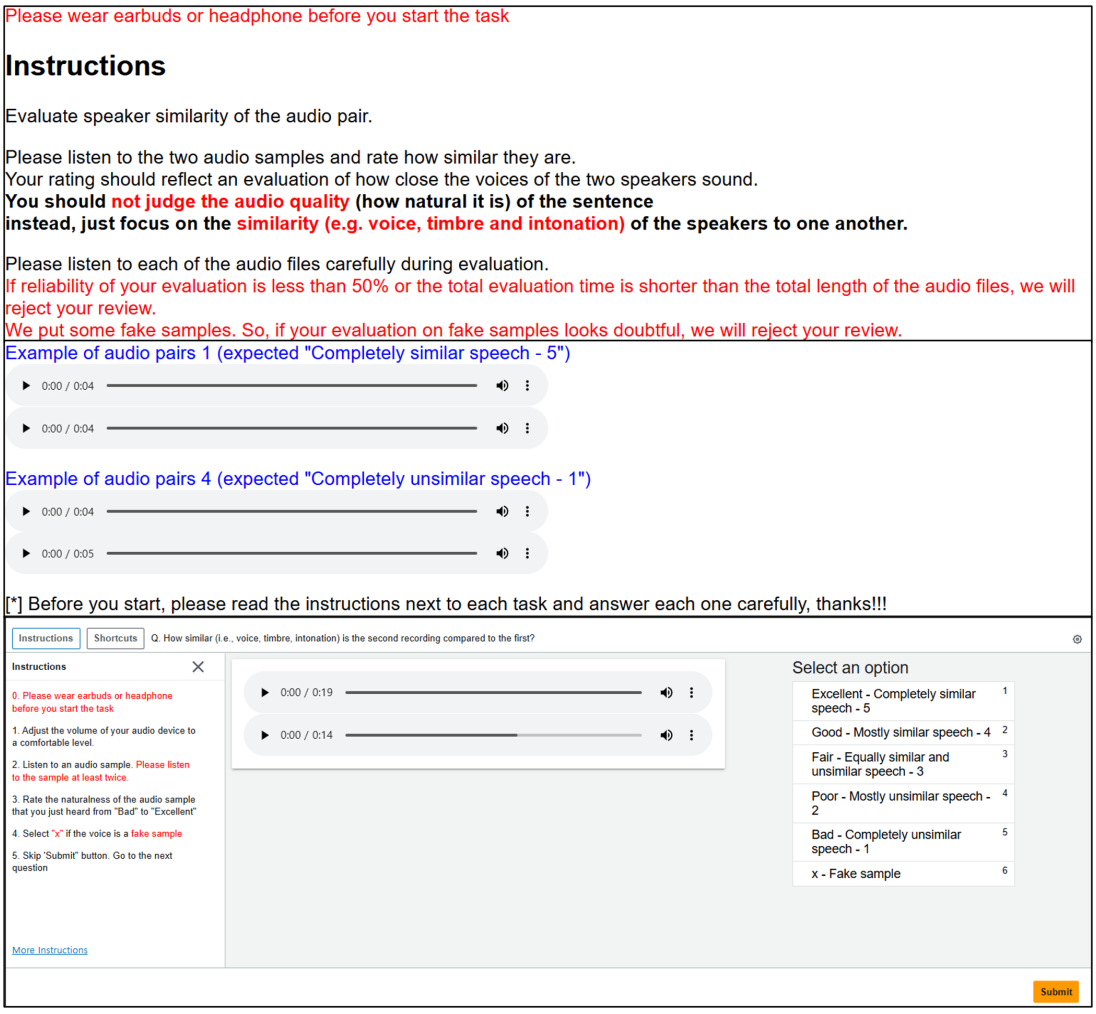

Figure 8: sMOS evaluation interface.