When Large Language Models Meet Speech:
A Survey on Integration Approaches

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Abstract

Recent advancements in large language models (LLMs) have spurred interest in expanding their application beyond text-based tasks. A large number of studies have explored integrating other modalities with LLMs, notably speech modality, which is naturally related to text. This paper surveys the integration of speech with LLMs, categorizing the methodologies into three primary approaches: text-based, latent-representation-based, and audio-token-based integration. We also demonstrate how these methods are applied across various speech-related applications and highlight the challenges in this field to offer inspiration for future research.

1 Introduction

In recent years, the field of natural language processing (NLP) has been greatly reshaped by the development of large language models (LLMs) (Brown et al., 2020; Touvron et al., 2023a; Google, 2024; Bai et al., 2023; DeepSeek-AI, 2024). These models have not only shown excellent ability in understanding and generating text but have also sparked interest in their potential applicability across other modalities, including speech. The integration of speech and LLMs offers a wide range of potential applications, including speech translation, conversational chatbots, and enhanced human-computer interaction in robotics.

Survey papers have reviewed speech language models (Peng et al., 2024; Cui et al., 2025), as well as audio language models (Latif et al., 2023) and multimodal language models (Ghosh et al., 2024a; Zhang et al., 2024b). However, there still lacks a survey specifically on the integration approaches of speech and LLMs, posing a challenge for researchers seeking to address this complex problem.

Distinct from other survey papers regarding speech and LLMs, this paper provides insight into
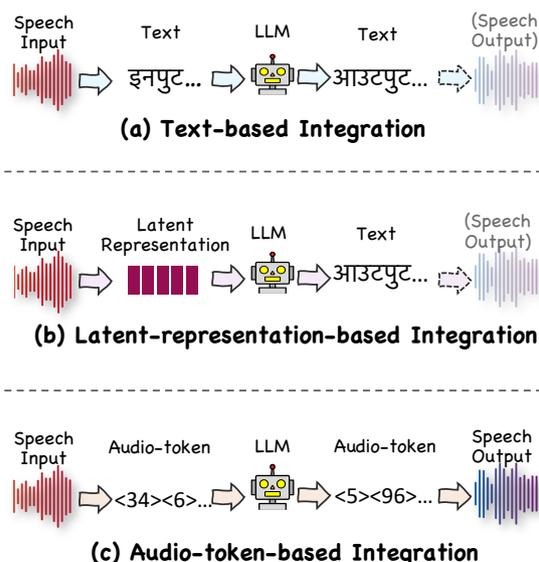

Figure 1: Overview of three fundamental approaches for speech–LLM integration.

the problem by specifically surveying the integration approaches of speech and LLMs. Studies on LLM tokenization (Chai et al., 2024; Tao et al., 2024) suggests that tokenization methods can affect the performance of LLMs. On the other hand, studies on tokenization methods for speech language modeling (Gat et al., 2023; Borsos et al., 2023) also show that speech tokenization methods can affect the performance of speech language models. In contrast to text processing, speech–LLM integration approaches are not limited to discrete tokenization, as presented in this paper. Therefore, studying the integration between speech and LLMs can be a key to innovations.

In this paper, we systematically categorize a substantial body of research on speech–LLM integration,[1] and provide a clear taxonomy of the integra-

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[1] One challenge that affects the scope of studies is the lack of standard definition for LLMs. In this paper, we adopt the loose definition by Zhao et al. (2023), focusing on models with over 10 billion parameters, while also including notable

tion approaches. We broadly categorize the integration into the following three types: (a) **Text-based integration**: LLMs process textual data, integrated with speech-to-text and/or text-to-speech models; (b) **Latent-representation-based integration**: Latent vector representations that encode speech data are utilized, mainly as inputs to LLMs; (c) **Audio-token-based integration**: Speech tokens, such as semantic tokens and/or acoustic tokens, are used as the inputs/outputs for LLMs. The overview of these approaches is illustrated in Figure 1, and the detailed taxonomy with representative studies is presented in Figure 2.

2 Background

2.1 Language Modeling

Language modeling dates back to statistical models like N-gram models (Brown et al., 1992), which were central to early NLP and automatic speech recognition (ASR) systems (Bahl et al., 1983). Neural-network-based language modeling was introduced by Bengio et al. (2000), formulating the probability

$$P(w_{1:T}) = \prod_{t=1}^{T} P(w_t|w_{1:t-1}),$$

where w_t is the t-th token (text subwords or speech tokens) and $w_{i:j} = (w_i, w_{i+1}, \cdots, w_j)$ is the subsequence from i-th token to j-th token.

Advances in hardware enabled neural models to scale, leading to innovations such as sequence-to-sequence learning (Sutskever et al., 2014) and the attention mechanism (Bahdanau et al., 2015). The Transformer architecture (Vaswani et al., 2017) revolutionalizes language modeling using self-attention by efficiently modeling long-range dependencies utilizing parallelized computation. Decoder-only Transformer (Liu et al., 2018) gains prominence through the multi-task learning paradigm with generative pre-training and discriminative fine-tuning (Radford et al., 2018). Scaling these models (Radford et al., 2019; Brown et al., 2020) shows generalization to multiple tasks without explicit supervision and achieves comparative performance against task-specific models, which leads to the advent of LLM era. Techniques such as instruction tuning (Wei et al., 2022) and alignment to human preference via reinforcement learning (Ouyang et al., 2022) further advance LLM capabilities. For a comprehensive overview of LLMs,

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studies with smaller models.

we refer the readers to LLM survey papers (Zhao et al., 2023; Minaee et al., 2024).

2.2 Speech Representations

Speech is captured as waveform signals, sampled at a specific sampling rate and quantization value, and represented as a sequence of amplitude values. For deep learning applications, they are often converted to speech representations with shorter sequence lengths, such as log Mel filterbanks, which we refer to as **filterbanks**. Following the success of the unsupervised pre-training approach in other fields, self-supervised speech models (S3Ms) (Baevski et al., 2020; Hsu et al., 2021; Chen et al., 2022) were introduced. These models predict masked frames to learn representations that capture phonetic information (Choi et al., 2024), along with a wide range of speech characteristics, such as speaker identity, paralinguistic information, and word-level information (Pasad et al., 2024). We refer to these contextualized frame-level features as **latent representations**.

To integrate speech (which is naturally continuous) with LLMs (which are designed to handle discrete tokens), **audio tokens** that are more discrete than previous representations have been studied recently. There are two mainstream approaches to modeling speech as audio tokens:[2] **semantic tokens** and **acoustic tokens**.[3] Semantic tokens can be obtained from S3Ms by discretizing latent representations using k-means. Acoustic tokens have been studied in the line of audio codecs (e.g., MP3 (ISO, 1993), Opus (Valin et al., 2012), etc.), which aim to compress audio signals. Neural audio codecs (Zeghidour et al., 2021; Défossez et al., 2023; Kumar et al., 2023) have recently gained traction as powerful tools to improve coding efficiency as well as perceptual quality. Because acoustic tokens exhibit better quality in producing output speech signals (Borsos et al., 2023) but fail to capture semantic information like semantic tokens do, recent studies combine both to obtain better representations for speech-language modeling (Wang et al., 2023d; Zhang et al., 2024c; Défossez et al., 2024).

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[2]Different studies use different terms for these tokens (e.g., Lakhotia et al. (2021) used the term "units" for semantic tokens). We use the terms semantic tokens and acoustic tokens as in Borsos et al. (2023) and the term audio tokens to represent either or both of them similar to Défossez et al. (2024).

[3]We note that there are other efforts than semantic or acoustic tokens to discretize speech signals (Bai et al., 2024a).

Speech-LLM Integration

Text-based (Sec. 3)
- Cascaded Integration (Sec. 3.1): AudioGPT (Huang et al., 2024a), HuggingGPT (Shen et al., 2023), Dighe et al. (2024b)
- LLM Rescoring (Sec. 3.2): Chen et al. (2023c), Udagawa et al. (2022), Li et al. (2023b), Hu et al. (2023), Huang et al. (2024b)
- LLM GER (Sec. 3.3): HyPoradise (Chen et al., 2023a), Yang et al. (2023a), GenTranslate (Hu et al., 2024c), Ma et al. (2023), Hu et al. (2024b), Whispering Llama (Radhakrishnan et al., 2023), MMGER (Mu et al., 2024), Yang et al. (2024a), Ko et al. (2024), LipGER (Ghosh et al., 2024b), Li et al. (2024b), Tang and Tung (2024), Chen et al. (2024a), Dighe et al. (2024a)

Latent-representation-based (Sec. 4)
- Convolutional Downsampling (Sec. 4.2.1): Hono et al. (2023), Yu et al. (2024), Fathullah et al. (2024), LTU (Gong et al., 2024), Pham et al. (2024), BLSP (Wang et al., 2023a), SALM (Chen et al., 2024e), WavLLM (Hu et al., 2024a), DeSTA (Lu et al., 2024), Llama-Omni (Fang et al., 2024), Seed-ASR (Bai et al., 2024b), SpeechVerse (Das et al., 2024), SLAM-ASR (Ma et al., 2024), Denisov and Vu (2024a), MaLa-ASR (Yang et al., 2024b), WHISMA (Li et al., 2024a), Lakomkin et al. (2024), Noroozi et al. (2024), Kang and Roy (2024), Li et al. (2024c), Chen et al. (2024a)
- CTC Compression (Sec. 4.2.2): Hono et al. (2023), Speech-Llama (Wu et al., 2023), Ling et al. (2024), Fathullah et al. (2023)
- Q-Former (Sec. 4.2.3): Yu et al. (2024), SALMONN (Tang et al., 2024), COSMIC (Pan et al., 2023), XLLM (Chen et al., 2023b), DeSTA (Lu et al., 2024), Secap (Xu et al., 2024a), BLSP-KD (Wang et al., 2024a), CoT-ST (Du et al., 2024a)
- Other Adaptation Methods: SLM (Wang et al., 2023c), Qwen-Audio (Chu et al., 2023), Qwen2-Audio (Chu et al., 2024), LauraGPT (Du et al., 2024b), LLaST (Chen et al., 2024d), BESTOW (Chen et al., 2024f), SALSA (Mittal et al., 2024), Ideal-LLM (Xue et al., 2024), Xu et al. (2024b), Chen et al. (2024a)

Audio-token-based (Sec. 5)
- Semantic Tokens (Sec. 5.1.1): VoxtLM (Maiti et al., 2024), SpeechGPT (Zhang et al., 2023), TWIST (Hassid et al., 2023), Spirit-LM (Nguyen et al., 2025), GPT-Talker (Liu et al., 2024), BASE TTS (Łajszczak et al., 2024), Llama-Omni (Fang et al., 2024), SpeechGPT-Gen (Zhang et al., 2024a), DiscreteSLU (Shon et al., 2024), PSLM (Mitsui et al., 2024), Cheng et al. (2024), VSP-LLM (Yeo et al., 2024), Xu et al. (2024b)
- Acoustic Tokens (Sec. 5.1.2): Hao et al. (2024), LauraGPT (Du et al., 2024b), Neekhara et al. (2024), Uniaudio (Yang et al., 2023b)
- Semantic and Acoustic Tokens (Sec. 5.1.3): AudioPaLM (Rubenstein et al., 2023), Moshi (Défossez et al., 2024), Hibiki (Labiausse et al., 2025), Emova (Chen et al., 2024b), Shen et al. (2024)
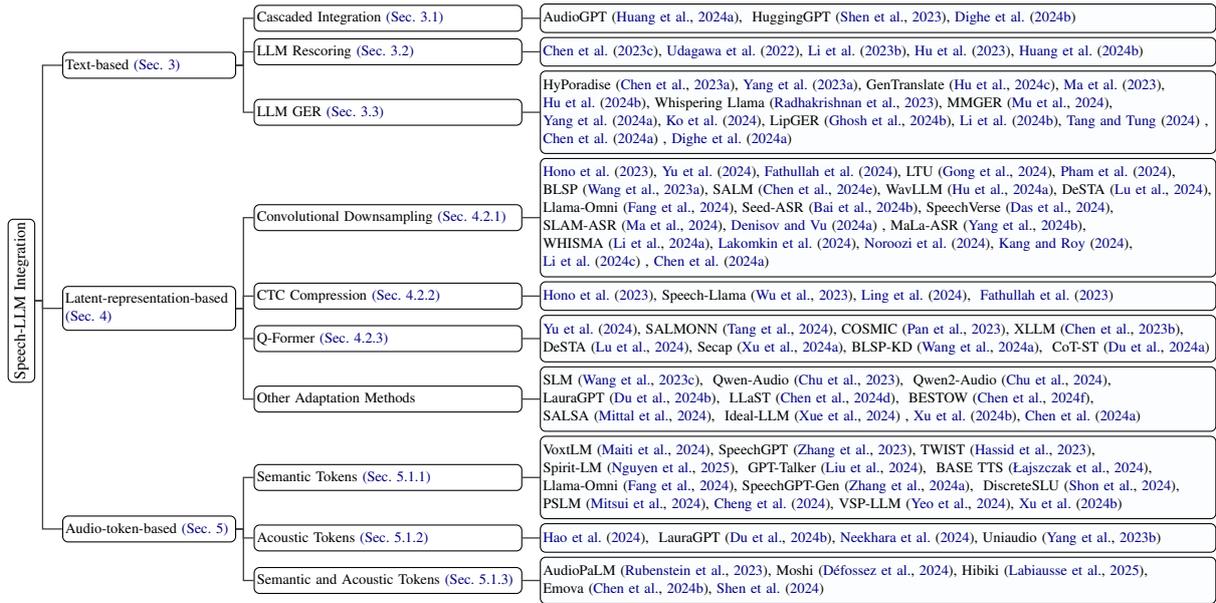
Figure 2: Taxonomy for speech-LLM integration. "Latent-representation-based" integration is categorized by different modality adaptation strategies. "Other Adaptation Methods" also includes studies that do not explicitly mention their modality adaptation methods.

3 Text-based Integration

This approach primarily utilizes text as both input and output for LLMs. One of the most direct implementations of this method is through **cascaded integration**, which is highly adaptable to various tasks. Within tasks like ASR, LLMs are not limited to working with the final recognition results but can also operate on intermediate hypotheses. This allows for sophisticated operations like **LLM rescoring**, and **LLM GER** (Generative Error Correction).

3.1 Cascaded Integration

Cascaded integration is the most simple and straightforward approach for integrating speech with LLMs. This involves the backbone LLM being supported by ASR and Text-to-Speech (TTS) interfaces for handling speech inputs and outputs, as well as the LLM invoking external models to solve speech-related tasks. This approach has been employed in models such as AudioGPT (Huang et al., 2024a) and HuggingGPT (Shen et al., 2023) to expand the applications of LLMs. The primary advantage of cascaded integration is its ease of implementation, allowing various tasks to be integrated into a single model with minimal effort. However, this method suffers from accuracy problems due to error propagation and efficiency problems due to the latency of processing through multiple steps.
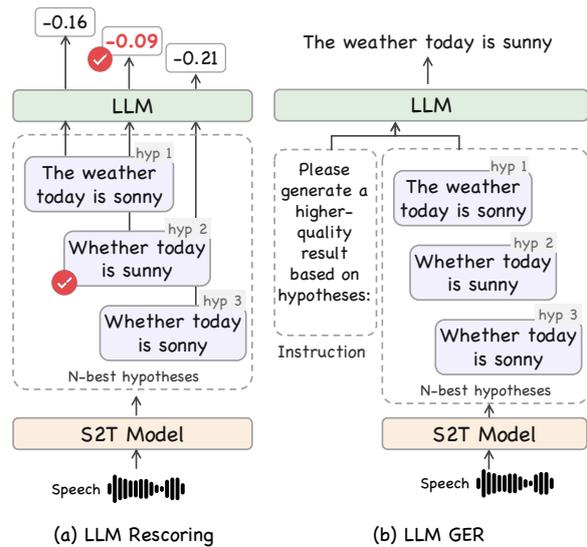
(a) LLM Rescoring

(b) LLM GER

Figure 3: Two text-based approaches using hypotheses for improving speech-to-text tasks.

3.2 LLM Rescoring

Before research on LLMs explosively expanded, ASR models had already begun using rescoring mechanisms with external language models to improve transcription accuracy (McDermott et al., 2019; Shin et al., 2019; Salazar et al., 2020; Xu et al., 2022). Recently, there have been efforts towards utilizing LLMs for rescoring, and it has been proven to be effective (Chen et al., 2023c; Udagawa et al., 2022).

As shown in Figure 3 (a), this process involves generating a list of n-best hypotheses $\mathcal{H} = \{Y_1, Y_2, ..., Y_n\}$ from the speech input X through the initial ASR decoding, which is then re-evaluated using an LLM to find the hypothesis with higher linguistic coherence to improve accuracy. The rescoring process can be expressed as

$$Y^* = \text{argmax}_{Y_i \in \mathcal{H}} \left[(1-\lambda) \log p_{\text{AM}}(Y_i|X) \right.$$
$$\left. + \lambda \log p_{\text{LLM}}(Y_i) \right]$$

where p_{AM} and p_{LLM} is the probability according to the ASR model (Acoustic Modle, AM) and the LLM, and λ is a weight balancing the contributions of two models.

3.3 LLM Generative Error Correction

Based on the concept of rescoring, LLM GER represents a new approach that fully utilizes the generative capability of LLMs. As shown in Figure 3 (b), the method utilizes an instructional prompt together with the n-best hypotheses list to guide the LLM in generating transcription predictions. Chen et al. (2023a) described this task performed by the LLM as hypotheses-to-transcription (H2T), which they explore under both fine-tuning and few-shot settings. Further studies have explored this direction with PEFT (Hu et al., 2024b) or in-context learning (Yang et al., 2023a; Ma et al., 2023).

Instead of merely selecting the best hypothesis from a pre-existing set, this method allows the LLM to generate a new transcription based on the hypotheses. By doing so, LLMs can potentially produce a result with a quality better than all initial hypotheses. Such an approach has proven to be well-suited for other tasks such as speech-to-text translation (S2TT), which require more generative capabilities of the model (Hu et al., 2024c). Lin et al. (2024) adopted the mixture-of-experts architecture (Fedus et al., 2022; Jiang et al., 2024) to let different experts handle different types of generative errors produced by task-specific models including ASR and ST models.

4 Latent-representation-based Integration

In this integration approach, a **speech encoder** is used to process the speech input and generate latent representations that are directly fed into the LLM, bypassing the embedding layer. The speech encoder is usually a Transformer-based model, which can be pre-trained on large-scale speech data or trained from scratch for the speech–LLM integration.

A critical issue of this approach is the sequence length gap between the speech and text modalities. Speech features, often sampled at rates of 50 to 100 frames per second, result in longer sequences compared to text tokens. Consequently, some form of **modality adaptation** mechanism is necessary to bridge these modalities, ensuring that the latent representations align with the LLM's embedding space.

4.1 Speech Encoder

For the speech encoder, various pre-trained models can be utilized to provide representations learned from large-scale speech data. This includes S3Ms (e.g. HuBERT (Hsu et al., 2021)) as well as the encoder of pre-trained ASR models (e.g. Whisper (Radford et al., 2023)). To connect the pre-trained speech encoder and the LLM, an *adapter* (also referred to as a *bridge network* or a *module connector*) is usually adopted.

An alternative approach is to train a speech encoder from scratch, specifically for the LLM integration. The structure of the speech encoder is usually a multi-layer Transformer (Vaswani et al., 2017) encoder or Conformer (Gulati et al., 2020).

4.2 Modality Adaptation

The modality adaptation mechanism is adopted for the speech encoder to map original frame-wise representations to token-wise representations. This allows the LLM to process the speech sequence in a manner similar to how it processes the text sequence, without having to deal with overly long sequences caused by long-form speech inputs.

The adaptation is usually accomplished by the adapter between pre-trained models, which is introduced in 4.1, or any part of the self-designed trained-from-scratch speech encoder. To this end, various adaptation methods have been proposed. Apart from some rarely-used strategies such as random downsampling (Wang et al., 2023c), most of the methods can be categorized into three groups, as shown in Figure 4: convolutional downsampling, CTC compression, and Q-former. According to comparisons conducted by Hono et al. (2023) and Yu et al. (2024), the Q-former generally outperforms convolutional downsampling, which in turn outperforms CTC compression. Next, we will detail these strategies in the following sections.
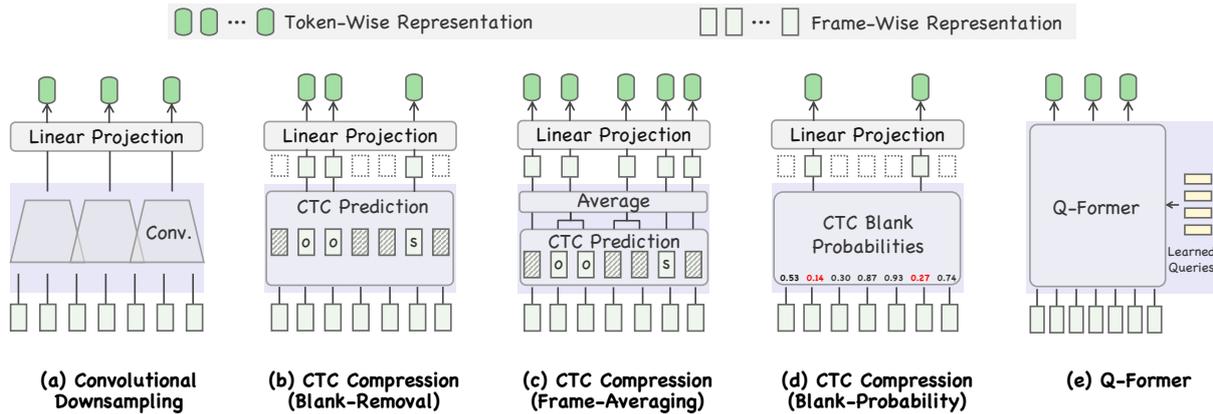
Figure 4: Different strategies for modality adaptation.

4.2.1 Convolutional Downsampling

A basic strategy where the speech representation sequence is downsampled from its original length using convolutional layers (Hono et al., 2023). When using the same number for kernel size and stride, it becomes equivalent to simply stacking multiple representation vectors together, which may only benefit parameter efficiency (Fathullah et al., 2024). For better alignment with the LLM's embeddings, some variants add a fully connected layer or a multi-head Transformer network after the convolutional layers (Yu et al., 2024).

4.2.2 CTC Compression

CTC compression involves two steps: (i) Training the speech encoder, or a part of it, on the ASR task based on Connectionist Temporal Classification (CTC) (Graves et al., 2013); (ii) Compressing the representation sequence based on the results of CTC predictions. Several specific strategies for the step (ii) include:

Blank-removal Discarding all the frames predicted as blanks (Hono et al., 2023; Wu et al., 2023).

Frame-averaging Averaging the latent representations of consecutive frames whose CTC predictions are the same label (Hono et al., 2023; Wu et al., 2023).

Blank-probability Discarding any frames with a CTC probability for blank exceeding a threshold (Ling et al., 2024).

4.2.3 Q-Former

Many studies (Yu et al., 2024; Tang et al., 2024; Pan et al., 2023) adopt Q-Former for the modality adaptation. Q-Former is a Transformer-based module converting variable-length input sequences into fixed-length output query representations. It is initially proposed for vision–text modality alignment (Li et al., 2023a).

4.3 Training Strategy

The optimal approach is to train the whole model consisting of the speech encoder and the LLM. However, fully fine-tuning the LLM is computationally expensive. Consequently, PEFT methods such as LoRA (Xu et al., 2024c), are often adopted to reduce resource consumption.

In scenarios where a pre-trained speech encoder is utilized, the primary focus is training the adapter connecting two pre-trained models. Whether to fine-tune the speech encoder or the LLM with PEFT seems optional as the decision differs across studies. On this topic, several studies (Hono et al., 2023; Pham et al., 2024) have conducted systematic investigations by comparing the effects of fine-tuning versus freezing different modules.

As for training the speech encoder from scratch, it is commonly done jointly with fine-tuning LLM with PEFT. Wu et al. (2023) proposed employing a two-stage training process where PEFT is not initiated until the speech encoder has undergone some initial training, ensuring a more stable training progression.

5 Audio-token-based Integration

As explained in Section 2.2, there are two types of audio tokens: semantic tokens and acoustic tokens. Studies use either or both, treating them as independent tokens like text or converting them back to latent representations. When semantic tokens are used for the output, a separate model to con-

vert them into filterbanks and to waveform signals similar to TTS models is often used.

5.1 Speech Language Models without LLMs

5.1.1 Semantic Token

Lakhotia et al. (2021) introduced the concept of generative spoken language modeling, which uses semantic tokens as both the input and output of a language model. Polyak et al. (2021) and Kharitonov et al. (2022) extended the idea by incorporating prosodic information. These models only used audio, and although they could output temporarily coherent contents, semantic understanding ability, and audio quality remained as challenges.

5.1.2 Acoustic Token

The use of acoustic tokens for language modeling was popularized in the task of TTS (Wang et al., 2023b; Chen et al., 2024c), where a few seconds of sample speech is used to generate coherent speech as those samples given text. Wang et al. (2023d) extended the idea to cover multi-tasking of ASR, machine translation (MT), and TTS.

5.1.3 Integration of Semantic and Acoustic tokens

AudioLM (Borsos et al., 2023) was introduced to incorporate both semantic and acoustic tokens. They adopted a two-stage approach, where the model first predicts semantic tokens and then subsequently predicts acoustic tokens. Zhang et al. (2024c) employed distillation from semantic representation to the first quantizer to combine semantic and acoustic tokens. Their generation approach is similar to Wang et al. (2023b), where an autoregressive model produces the first-layer token and a non-autoregressive model produces the rest.

5.2 Integration of LLMs into Speech Language Models

The use of LLMs as an underlying model of speech language models has become more popular following the success of LLMs. Hassid et al. (2023) showed that training speech language models using underlying pretrained text language models could improve performance. VoxtLM (Maiti et al., 2024) uses OPT (Zhang et al., 2022) as an underlying LLM and conducts multi-task fintuning it on ASR, TTS, and language modeling on text and semantic tokens. AudioPaLM (Rubenstein et al., 2023) adopts a similar approach to Borsos et al. (2023) but also enables text input/output, leveraging PaLM

(Chowdhery et al., 2023) as the underlying LLM. TWIST and SpeechGPT (Zhang et al., 2023) use Llama (Touvron et al., 2023a) as the underlying model and use semantic tokens as both input and output. Spirit-LM (Nguyen et al., 2025) uses Llama 2 (Touvron et al., 2023b) as the underlying model and uses a mixture of semantic and text tokens for both input and output.

Défossez et al. (2024) introduced a new architecture for speech language modeling. Similarly to previous studies, they trained a text LLM and a codec model similar to Zhang et al. (2024c). Their architecture enables duplex ability of listening and generating speech by using a hierarchical autoregressive model consisting of two Transformer modules, namely Temporal Transformer and Depth Transformer (Lee et al., 2022). This architecture is also shown to be effective for speech-to-speech translation (S2ST) (Labiausse et al., 2025).

6 Comparative Analysis

6.1 Advantages and Disadvantages

It is important to understand the advantages and disadvantages of the three integration approaches when employing them for different applications. We summarize their pros and cons as follows:

- **Degree of integration:** Latent-representation-based > Audio-token-based > Text-based.
- **Interpretability:** Text-based > Audio-token-based > Latent-representation-based.
- **Speech generation ability:** Text-based and audio-token-based approach can generate speech, whereas latent-representation-based approaches typically cannot.

Based on these characteristics, different approaches excel in different scenarios:

- Latent-representation-based and audio-token-based approaches are better than text-based approach, in scenarios where sufficient resources (data, computational power, and time) are available or when real-time processing is required. Deeper integration reduces error propagation and latency but demands more extensive resources.
- Text-based approach is better than latent-representation-based and audio-token-based approaches, in scenarios where resources are limited or when greater interpretability is required.
- Latent-representation-based approach is better than audio-token-based, in scenarios where

Task	Dataset	Metric	Model	Integration Method	Performance
ASR	**Librispeech** *dev-clean | dev-other | test-clean | test-other*	WER ↓	Whisper-large-v2 (Radford et al., 2023)	Non-LLM	— | — | 2.7 | 5.2
			HyPoradise (Chen et al., 2023a)	Text-based → LLM GER	— | — | 1.8 | 3.7
			BLSP (Wang et al., 2023a)	Latent-representation-based → Convolutional Downsampling	— | — | 10.4 | —
			SpeechVerse (Das et al., 2024)	Latent-representation-based → Convolutional Downsampling	— | — | 2.1 | 4.4
			Seed-ASR (Bai et al., 2024b)	Latent-representation-based → Convolutional Downsampling	— | — | **1.5** | **2.8**
			SALMONN (Tang et al., 2024)	Latent-representation-based → Q-Former	— | — | 2.1 | 4.9
			SLM (Wang et al., 2023c)	Latent-representation-based → Other Adaptation Methods	— | — | 2.6 | 5.0
			Qwen-Audio (Chu et al., 2023)	Latent-representation-based → Other Adaptation Methods	1.8 | 4.0 | 2.0 | 4.2
			Qwen2-Audio (Chu et al., 2024)	Latent-representation-based → Other Adaptation Methods	**1.3** | **3.4** | 1.6 | 3.6
			LauraGPT (Du et al., 2024b)	Latent-representation-based → Other Adaptation Methods	— | — | 1.4 | 7.7
			SpeechGPT-Gen (Zhang et al., 2024a)	Audio-token-based → Semantic Token	— | — | 2.4 | —
			SLAM-ASR (Ma et al., 2024)	Latent-representation-based → Convolutional Downsampling	— | — | 1.9 | 3.8
			BESTOW (Chen et al., 2024f)	Latent-representation-based → Other Adaptation Methods	— | — | — | 3.2
			Hao et al. (2024)	Audio-token-based → Acoustic Tokens	3.7 | 6.6 | 3.4 | 7.1
	Fleurs *zh | en*	WER ↓	Whisper-large-v2 (Radford et al., 2023)	Non-LLM	4.2 | 14.7
			Huang et al. (2024b) w/ PaLM2	Text-based → LLM Rescoring	13.1 | —
			Seed-ASR (Bai et al., 2024b)	Latent-representation-based → Convolutional Downsampling	**3.43** | —
			Qwen2-Audio (Chu et al., 2024)	Latent-representation-based → Other Adaptation Methods	— | 7.5
			DiscreteSLU (Shon et al., 2024)	Audio-token-based → Semantic Token	12.6 | —
	AISHELL-2 *Mic | iOS | Android*	WER ↓	Seed-ASR (Bai et al., 2024b)	Latent-representation-based → Convolutional Downsampling	**2.2** | **2.2** | **2.2**
			Qwen-Audio (Chu et al., 2023)	Latent-representation-based → Other Adaptation Methods	3.3 | 3.1 | 3.3
			Qwen2-Audio (Chu et al., 2024)	Latent-representation-based → Other Adaptation Methods	3.0 | 3.0 | 2.9
			LauraGPT (Du et al., 2024b)	Latent-representation-based → Other Adaptation Methods	— | 3.2 | —
	VoxPopoli *All*	WER ↓	SpeechVerse (Das et al., 2024)	Latent-representation-based → Convolutional Downsampling	6.5
			AudioPaLM (Rubenstein et al., 2023)	Audio-token-based → Semantic and Acoustic Tokens	9.8
S2TT	**CoVoST2** *en-de | de-en |* *en-zh | zh-en |* *es-en | fr-en |* *it-en | ja-en*	BLEU ↑	Whisper-large-v2 (Radford et al., 2023)	Non-LLM	— | 36.3 | — | 18.0 | 40.1 | 36.4 | 30.9 | 26.1
			GenTranslate (Hu et al., 2024c)	Text-based → LLM GER	— | 39.2 | — | 21.6 | 42.0 | 41.7 | — | 22.9
			GenTranslate-V2 (Hu et al., 2024c)	Text-based → LLM GER	— | 40.6 | — | 23.3 | 43.6 | 42.7 | — | 25.4
			BLSP (Wang et al., 2023a)	Latent-representation-based → Convolutional Downsampling	24.4 | — | 41.3 | — | — | — | — | —
			Speech-Llama (Wu et al., 2023)	Latent-representation-based → CTC Compression	— | 27.1 | — | 12.3 | 27.9 | 25.2 | 25.9 | 19.9
			SALMONN (Tang et al., 2024)	Latent-representation-based → Q-Former	18.6 | — | 33.1 | — | — | — | — | —
			Qwen-Audio (Chu et al., 2023)	Latent-representation-based → Other Adaptation Methods	25.1 | 33.9 | 41.5 | 15.7 | 39.7 | 38.5 | 36.0 | —
			Qwen2-Audio (Chu et al., 2024)	Latent-representation-based → Other Adaptation Methods	**29.9** | 35.2 | **45.2** | 24.4 | 40.0 | 38.5 | 36.3 | —
			LauraGPT (Du et al., 2024b)	Latent-representation-based → Other Adaptation Methods	— | 38.5 | — | — | — | — | — | —
			LLaST (Chen et al., 2024d)	Latent-representation-based → Other Adaptation Methods	— | 41.2 | — | 24.8 | **46.1** | **45.1** | **43.0** | **28.8**
			AudioPaLM (Rubenstein et al., 2023)	Audio-token-based → Semantic and Acoustic Tokens	— | **43.4** | — | **25.5** | 44.2 | 44.8 | — | 25.9
			Ideal-LLM (Xue et al., 2024)	Latent-representation-based → Other Adaptation Methods	25.9 | 38.5 | — | — | 41.5 | 40.0 | 38.0 | —
S2ST	**CVSS S2ST** *de-en | zh-en |* *es-en | fr-en |* *it-en | ja-en*	ASR-BLEU ↑	Translatotron 2 + pretraining + TTS aug (Jia et al., 2022)	Non-LLM	33.6 | 13.1 | 38.5 | 36.5 | 35.7 | 8.5
			AudioPaLM (Rubenstein et al., 2023)	Audio-token-based → Semantic and Acoustic Tokens	**37.2** | **20.0** | **40.4** | **38.3** | **39.4** | **20.9**
TTS	**AISHELL-1**	CER ↓ | SECS ↑ | MOSNet ↑	VALL-E Phone (Wang et al., 2023b)	Non-LLM	**4.75** | **0.91** | **3.22**
			VALL-E Token (Wang et al., 2023b)	Non-LLM	6.52 | **0.91** | 3.19
			LauraGPT (Du et al., 2024b)	Audio-token-based → Acoustic Tokens	6.91 | 0.90 | 3.14
	LibriTTS	WER ↓ | SECS ↑ | MOSNet ↑	VALL-E Phone (Wang et al., 2023b)	Non-LLM	**4.30** | 0.92 | 3.28
			VALL-E Token (Wang et al., 2023b)	Non-LLM	6.57 | **0.93** | 3.28
			SpeechGPT-Gen (zero-shot) (Zhang et al., 2024a)	Audio-token-based → Semantic Token	3.10 | 0.63 | 3.63
			VoxtLM (Maiti et al., 2024)	Audio-token-based → Semantic Token	— | — | **4.36**
			LauraGPT (Du et al., 2024b)	Audio-token-based → Acoustic Tokens	8.62 | 0.91 | 3.26
	Topic-StoryCloze	TSC ↑	Spirit-LM (Nguyen et al., 2025)	Audio-token-based → Semantic Token	82.9
			TWIST-1.3B (Hassid et al., 2023)	Audio-token-based → Semantic Token	70.6
			TWIST-7B (Hassid et al., 2023)	Audio-token-based → Semantic Token	74.1
			TWIST-13B (Hassid et al., 2023)	Audio-token-based → Semantic Token	76.4
			Moshi (Défossez et al., 2024)	Audio-token-based → Semantic and Acoustic Tokens	**83.6**
	StoryCloze	SSC ↑	Spirit-LM (Nguyen et al., 2025)	Audio-token-based → Semantic Token	61.0
			TWIST-1.3B (Hassid et al., 2023)	Audio-token-based → Semantic Token	52.4
			TWIST-7B (Hassid et al., 2023)	Audio-token-based → Semantic Token	55.3
			TWIST-13B (Hassid et al., 2023)	Audio-token-based → Semantic Token	55.4
			Moshi (Défossez et al., 2024)	Audio-token-based → Semantic and Acoustic Tokens	**62.7**

Table 1: Quantitative comparison based on applications. The **Bold** denotes the best result.

speech is only considered as input. Latent-representation-based methods provide the deepest integration when generating textual or other downstream outputs.

- Audio-token-based is better than latent-representation-based, in scenarios where speech is also considered as output. Generating speech from latent representations remains challenging, making audio-token-based approaches more suitable in these cases.

6.2 Quantitative Comparison

We provide a comprehensive performance comparison in Table 1, comparing studies with different integration approaches across multiple tasks: ASR, S2TT, S2ST, and TTS. The table highlights key metrics such as word error rate (WER) and BLEU, alongside each model's integration method and backbone components.

While Table 1 summarizes many state-of-the-art results, direct comparisons can be challenging due to variations in backbone LLMs, acoustic front-ends, and training protocols. For instance, although BLEU scores on CoVoST 2 (Wang et al., 2021) indicate that deeper integration methods (e.g., latent-representation-based) often yield improved performance, model size and training resources also play a significant role. Future work should focus on more uniform experimental conditions to isolate the impact of each approach.

Nonetheless, the metrics in Table 1 serve as a starting point for evaluating how well each method handles different tasks. The results suggest that deeper integration (e.g., latent-representation-based) can be beneficial when sufficient computational resources and training data are available, whereas text-based methods often offer greater interpretability and simpler pipelines.

6.3 Computational Trade-offs

As different methods have different computational requirements, it is difficult to have direct comparisons through a literature review. For numerical comparisons, comparing different approaches with a standard setting is required, which is one future direction. That said, we provide an overview of the computational requirements per category below:

- For text-based integration, the computational cost is equivalent to that of running separate models for ASR, LLM, and TTS. Rescoring based on N-best list increases the inference compute by a constant factor. For generative error correction, studies have explored full fine-tuning, parameter-efficient fine-tuning, and mixture-of-experts of LLMs. Parameter-efficient fine-tuning can provide better performance compared to full fine-tuning (Chen et al., 2023a). Mixture-of-experts requires high memory and computation for training, but shows good performance in handling multiple tasks with light inference.

- For latent-representation-based integration, speech encoders are connected to LLMs through adapters. These adapters are lightweight, and studies have explored full fine-tuning and parameter-efficient fine-tuning, including freezing a part of the models. Pham et al. (2024) showed that applying LoRA to the LLM significantly enhances the performance, and for the encoder module, full fine-tuning yields the best performance, followed by partial fine-tuning, while partial fine-tuning is more cost-effective.

- For audio-token-based integration, it involves audio token encoding/decoding and language modeling with audio tokens. For semantic tokens, feature extraction from S3Ms and training/assignment steps of k-means is required. They are lightweight compared to language modeling (the largest S3Ms have about 2B parameters), but efficient implementation is required for large-scale data. If the output is speech, a vocoder to convert semantic tokens to waveforms is required, which is also relatively lightweight compared to language modeling. For acoustic tokens, encoding and decoding are done using the same model, and the inference is lightweight. Computational cost for language modeling is similar to that of text-based ones.

Overall, we can argue that the computational cost is bottlenecked by the size of the LLM that is used. Text-based integration and audio-token-based integration would require roughly the same computational bottleneck by LLMs, while latent-representation-based integration requires handling both the speech encoder and LLMs at the same time.

7 Challenges

7.1 Text-based Integration

Text-based integration preserves the original LLM input modality, which is text. Because the model is already optimized for textual inputs, this approach typically requires the least adaptation from the LLM. However, transforming speech into text before feeding it into the LLM inevitably introduces a layer of abstraction and potential information loss such as prosody and emotion, which limits the downstream performance.

Therefore, the main challenge is how to convey the rich information of source speech through text. In current practice, the intermediate text is often generated based on the highest probability (Chen et al., 2023a; Yang et al., 2023a; Radhakrishnan et al., 2023). Although this strategy maximizes intermediate accuracy, it may not be optimal for the LLM and its final outputs. One possible direction is to inject controlled randomness during decoding to ensure additional diversity. However, degrading accuracy could also have a negative effect, creating a trade-off. How to balance diversity and accuracy remains an open research question that requires future investigation.

7.2 Latent-representation-based Integration

In contrast to text-based integration, latent-representation-based integration employs an intermediate representation closer to the source speech but more distant from the LLM's native input space. Consequently, the primary challenge lies in aligning these acoustic representations with the textual embedding space of the LLM. Section 4.2 introduces multiple modality adaptation mechanisms to address this and enable LLMs to handle speech more effectively.

While the primary focus of most research introduced in this paper has been on adapting LLMs to handle speech data better, there is comparatively less attention on how these adaptations affect performance on text-based tasks. The alignment of

text and speech data, along with their latent representations, remains underexplored, with only a few studies focusing on this issue (Wang et al., 2023a; Lu et al., 2024).

A promising solution for improving speech-text alignment is the generation of high-quality synthetic speech data to supplement real datasets, thus closing the gap between the speech modality and text-based LLMs. More thorough investigations into how to align speech and text representations in complex languages (beyond English) could also strengthen the multimodal capabilities of LLMs.

7.3 Audio-token-based Integration

As stated in Sections 2.2 and 5, S3Ms (and their derived semantic tokens) mainly capture phonetic information (Choi et al., 2024), while acoustic tokens offer higher fidelity in generating speech signals (Borsos et al., 2023).

Integrating both representations, as presented in Section 5.1.3, is one approach that requires further investigation. While this approach achieves strong performance across various downstream tasks (Table 1), there are still limited studies on this approach, where the models are English-centric models that rely on millions of hours of speech data. Minimizing computational requirements is essential to extend this approach to languages lacking the vast resources available for English.

Some studies suggest that latent-representation-based integration can outperform audio-token-based integration (Wang et al., 2024b). However, it is possible that this is due to the suboptimal representation of audio tokens (Gat et al., 2023), requiring further improvement of tokenization methods and comparison with other integration approaches.

7.4 Fair Comparison Across Integration Approaches

Beyond these integration-approach-specific challenges, there is a notable gap in comparing the different integration approaches under a unified setting. Most existing works focus on one approach, making it difficult to assess their relative merits consistently. A fair comparison among these integration methods could clarify how different factors affect performance. Developing standardized benchmarks, protocols, and reporting practices for speech–LLM research would help future work isolate the core differences between these approaches.

7.5 Multilingualism

The challenge of multilingualism in speech–LLM integration is also significant. Most existing speech–LLM models are designed to handle only English, which limits their range of applicability. Although there are studies focusing on multilingual capabilities (Hu et al., 2024c, 2023; Huang et al., 2024b), the majority still rely on English-centric LLMs. Only a small fraction of research efforts (Denisov and Vu, 2024b) explicitly consider the multilingualism of pre-trained LLMs. However, the effectiveness of a speech–LLM model is often constrained by the quality of the text-based backbone LLM. This dependency implies that any limitations in the backbone LLMs, especially in terms of handling multiple languages, can directly impact the performance of speech LLMs.

7.6 Real-time Processing

Real-time processing presents another substantial challenge in the field of speech–LLM integration. Compared to text-based applications, speech-based applications such as ST more often require real-time processing to be practical in everyday use. However, the large size of LLMs typically leads to increased latency, which can neutralize some of the benefits gained from improved accuracy. While most speech LLMs are capable of handling tasks offline, there is a need for more innovative methods that can facilitate online processing. Deeper integration with latent representations or audio tokens tends to result in lower latency compared to text-based approaches. Recent models that focus on real-time applications, such as Moshi (Défossez et al., 2024), show promising starts in addressing this challenge. Developing such methods would significantly enhance the utility of LLMs in real-time speech applications, making them more viable for real-world usage.

8 Conclusion

In this survey, we systematically categorize the integration of LLMs with speech modality, outlining three primary approaches: text-based, latent-representation-based, and audio-token-based integration. Each method demonstrates unique strengths in performing different speech-related tasks. However, numerous challenges remain in this evolving field, presenting significant opportunities for future research.

Limitations

In our survey of the integration of speech with LLMs, we have covered the significant developments within this field. Despite our comprehensive approach, we acknowledge that the rapid pace of development in speech processing and LLM means that some recent advances or discussions might have escaped our attention and are not fully addressed within this paper.

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