From TOWER to SPIRE: Adding the Speech Modality to a Text-Only LLM

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Abstract

We introduce SPIRE, a speech-augmented language model (LM) capable of both translating and transcribing speech input from English into 10 other languages as well as translating text input in both language directions. SPIRE integrates the speech modality into an existing multilingual LM (MLM) via speech discretization and continued pre-training using only 42.5K hours of speech. In particular, we adopt the pretraining framework of MLMs and treat discretized speech input as an additional *translation language*. This approach not only equips the MLM with speech capabilities, but also preserves its strong text-only performance. We achieve this using significantly less data than existing speech LMs, demonstrating that discretized speech input integration as an additional language is feasible during LM adaptation. We will make our code and models available to the community.

1 Introduction

Large language models (LLMs) have demonstrated remarkable success on various text-based natural language processing tasks (Achiam et al., 2023; Touvron et al., 2023; Yang et al., 2024; Alves et al., 2024; Martins et al., 2024), motivating research into extending them to other modalities. This has led to the development of multimodal LMs (MLMs) capable of processing speech, audio, images, and video (Team et al., 2023; Driess et al., 2023; Rubenstein et al., 2023; Liu et al., 2023; Tang et al., 2024; Défossez et al., 2024; Hu et al., 2024; Huang et al., 2024; Nguyen et al., 2025). However, the integration of new modalities often come at the cost of existing capabilities (Zhai et al., 2024).

For speech-LLM integration, a simple approach is to link the output of an automatic speech recognition (ASR) system to a text-only LLM (Huang et al., 2024). This solution, however, is prone to error propagation and depends largely on individual model quality. More popular are solutions that investigate equipping LLMs natively with speech processing capabilities through modality projection (Shu et al., 2023; Radhakrishnan et al., 2023; Wu et al., 2023a; Tang et al., 2024; Xue et al., 2024; Hu et al., 2024). Typically, a speech foundation model generates speech representations that are mapped to the embedding space of the LLM, following which the model is then fine-tuned along with a projector on speech-to-text tasks to equip the LLM with speech processing capabilities. In this setting, key challenges include prompt overfitting and high training costs, as tuning these MLMs requires the adaptation of the speech projector module on vast amounts of raw speech data (Tang et al., 2024; Hu et al., 2024).

An alternative approach for MLMs is to use *speech discretization*, where continuous speech features are transformed prior to training into sequences of "discrete speech units" (DSUs), which can be processed similarly to text (Chou et al., 2023a; Zhang et al., 2023; Rubenstein et al., 2023; Chang et al., 2024; Défossez et al., 2024; Trinh et al., 2024; Maiti et al., 2024; Nguyen et al., 2025). This approach simplifies training by eliminating the need for additional parameters beyond extended embedding matrices. Finally, while both projector-based and discretization-based MLMs have shown promising results on text-to-speech and speech-to-text tasks, their development has prioritized speech-centric tasks at the expense of textual performance. Furthermore, limited research has focused on integrating speech while preserving the LLM's original capabilities in textual tasks (Chou et al., 2023b; Huang et al., 2024).

In this work we present SPIRE, a speech-augmented LLM built from the open-weight multilingual model TOWER (Alves et al., 2024). SPIRE can perform English ASR and from-English speech translation (ST) while maintaining TOWER's strong performance on machine translation (MT) across

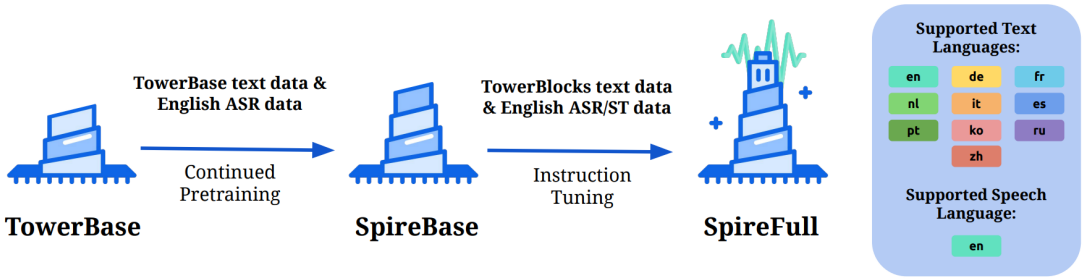

Figure 1: Illustration of the model training method for SPIREBASE and SPIREFULL.

all 10 languages[1] supported by TOWER. SPIRE encodes speech via HuBERT-based (Hsu et al., 2021) k-means clustering, as in previous work (Zhang et al., 2023; Rubenstein et al., 2023; Chang et al., 2024). We perform training in two stages: Continued Pre-Training (CPT) and Instruction Tuning (IT). For the CPT stage, we use a mixture of ASR data and a small fraction of TOWER's text CPT data. For IT, we leverage TOWER's task-specific MT data, as well as additional English ASR and ST data. SPIRE is trained using only **42.5K** hours of speech, differing from the large scale of data used by existing models (Radford et al., 2023; Nguyen et al., 2025; Chu et al., 2024). Figure 1 illustrates our training process. We make the following contributions:

- We present a pipeline for integrating speech as an additional modality into an existing LLM, enabling it to transcribe and translate English speech while preserving its original text-only capabilities across 10 languages;
- We analyze speech integration at two stages, namely CPT and IT, demonstrating the necessity of both stages to achieve optimal performance across both modalities;
- We make our models, datasets, and scripts available to the community.[2]

2 Related Work

Speech-to-Text Models An increasing number of studies have explored integrating speech into LLMs (Zhang et al., 2023; Rubenstein et al., 2023; Hassid et al., 2024). For discrete speech input, Hassid et al. (2024) demonstrate the benefits of initializing a speech LLM from a text-based LLM. SpeechGPT (Zhang et al., 2023) applies IT on speech-to-text cross-modal ASR, text-to-speech (TTS), and text-based question answering. AudioPALM (Rubenstein et al., 2023) is trained in a multi-task fashion, similarly to SpeechGPT, but on multilingual input. Recently, VoxtLM (Maiti et al., 2024) was trained jointly on DSUs and text data for ASR, TTS, and open-ended speech/text generation. Our work is most similar to Spirit-LM (Nguyen et al., 2025), which adapts an LLM with an interleaved mixture of DSU and text data, which requires an expensive DSU-to-transcript step to create. In contrast, we adopt a more cost-effective input representation that can be extended to any language, regardless of the availability of a speech aligner. Our focus is on successfully incorporating speech input while preserving the original competence of the model, so that the resulting model can successfully perform both speech-to-text and text-only tasks. None of the aforementioned models are trained to preserve the original model's performance in text tasks.

Adapting LLMs Previous approaches involve training from scratch with task- and domain-specific data (Singhal et al., 2023; Lewkowycz et al., 2022), performing CPT with a diverse training data mix designed to broadly extend the model's knowledge (Wu et al., 2023b), or instruction tuning on use-case-specific data (Chen et al., 2023). Recent work has explored combining the latter two approaches (Xu et al., 2024a; Alves et al., 2024; Wei et al., 2021; Roziere et al., 2023). In our approach to integrating DSUs into TOWER, we take inspiration from Alves et al. (2024) in adopting a two-step CPT+IT process. Our work differs in that we focus on adding the speech modality, whereas Alves et al. (2024) focused on increasing the multilingual capabilities of an LLM.

Continuous and Discrete Speech Representations Self-supervised speech representation models produce contextualized high-dimensional

[1] en, de, fr, nl, it, es, pt, ko, ru, zh
[2] [REDACTED]

speech vectors directly from raw audio (Hsu et al., 2021; Baevski et al., 2020; Chen et al., 2022), largely outperforming statistical speech features on downstream tasks (Yang et al., 2021). These continuous representations can be used to derive DSUs that capture both linguistic content and prosody through clustering (Borsos et al., 2023; Kharitonov et al., 2022). DSUs provide better alignment with textual data, facilitating the transfer of successful training settings from the text domain (Cui et al., 2024). Building on Lakhotia et al. (2021), which demonstrated that HuBERT (Hsu et al., 2021) is a powerful feature extractor, several studies have adopted this approach, incorporating a k-means clustering step for discretization (Zhang et al., 2023; Rubenstein et al., 2023; Lam et al., 2024; Chang et al., 2024; Nguyen et al., 2025). Xu et al. (2024b) study the optimal settings to obtain DSUs in terms of cluster size and feature extraction layer. We use their findings to inform our initial choices.

3 SPIRE: A Speech-to-Text LLM

We introduce SPIRE, whose goal is to equip an LLM with speech capabilities while preserving its preexisting text capabilities. As our base LLM we choose TOWER (Alves et al., 2024), which was developed from Llama-2 (Touvron et al., 2023) with a two-step approach: CPT on a mixture of monolingual and parallel data (TOWERBASE), followed by IT on translation-related tasks (TOWERINSTRUCT). We use an approach similar to TOWER to extend the model to the speech modality. First, we perform CPT with a combination of text-only and aligned speech-to-text datasets, followed by IT using both text-only general-purpose and task-specific data curated in TOWERBLOCKS,[3] alongside task-specific speech-to-text datasets.

We choose TOWER in particular due to its competitive performance compared to other open alternatives. TOWER-based models were among the best participating systems in the WMT24 general translation task (Kocmi et al., 2024). TOWER's usage of open source data during the CPT phase along with the release of the TOWERBLOCKS dataset, used in the IT phase, further motivates our choice.

3.1 Speech Discretization

To easily transfer the training set-up of TOWER, we use DSUs as opposed to an auxiliary speech encoder. For all speech datasets that were used, we follow recent discretization methodology (Zhang et al., 2023; Rubenstein et al., 2023; Chang et al., 2024) to produce DSUs by first extracting continuous speech representations for our speech data from the 22nd layer of an HuBERT-large model, trained on 60K hours of English speech (Hsu et al., 2021), and then using k-means clustering ($K = 5000$) to produce centroids that are used to convert our continuous speech representation into a discrete sequence of cluster IDs.[4] We train our k-means model on a collection of 235K audio files (approximately 720 hours), drawn from three speech corpora: CoVoST-2 (Wang et al., 2021b), VoxPopuli (Wang et al., 2021a), and Multilingual Librispeech (MLS; Pratap et al., 2020). The CoVoST subset consists of 62K audio files from 10,049 speakers, with a maximum of 8 audio files per speaker. The VoxPopuli subset includes 65K audio files from 639 speakers, capped at 250 audio files per speaker. Finally, the MLS subset contains 107K audio files from 5,490 speakers.

3.2 SPIREBASE

The first CPT stage, yielding SPIREBASE, is trained from TOWERBASE-7B[5] using both text-only and aligned speech-to-text datasets. Following previous work, we include a fraction of TOWER's original training data to preserve its existing performance (Scialom et al., 2022; de Masson D'Autume et al., 2019).

3.2.1 Data

We use a mixture of monolingual and parallel text in Chinese (zh), Dutch (nl), English (en), French (fr), German (de), Italian (it), Korean (ko), Portuguese (pt), Russian (ru), and Spanish (es), that was sourced from the TOWER training data, as well as English ASR data sourced from popular open-source ASR datasets, as reported in Table 1. Both speech and text data are downsampled to create a 6B token data mixture (5B speech; 1B text), measured by the model tokenizer.[6] Note that the 5B speech tokens include both DSUs (4.4B tokens) and their text transcriptions (0.6B tokens).

[3] https://huggingface.co/datasets/Unbabel/TowerBlocks-v0.2

[4] Optimizing the layer selection for feature extraction is a complex research problem (Pasad et al., 2023; Mousavi et al., 2024). In this work we follow the insights from Gow-Smith et al. (2023) and Xu et al. (2024b).

[5] We used TOWER-7B models instead of the 13B or 70B versions due to its lower compute requirements

[6] Preliminary experiments on the data mixture led to this particular choice.

Text Data The monolingual text data split corresponds to data from mC4 (Raffel et al., 2019), a multilingual web-crawled corpus which we uniformly sample from across all languages. The parallel data split includes uniformly sampled instances to and from English (en↔xx) for the 10 languages, sourced from various public sources. Further details can be found in Alves et al. (2024).

Speech Data We collect 35K hours of speech data from SPGI Speech (O'Neill et al., 2021), GigaSpeech (Chen et al., 2021), MLS, and VoxPopuli. We normalize as described in Appendix A.1.

3.2.2 CPT Setup

We train SPIREBASE using MegatronLLM (Cano et al., 2023) on 8 A100-80GB GPUs for 6 days. We use the same hyperparameters as TOWER, except for the effective batch size, which in our case is 2,304. To incorporate the DSUs in the CPT stage, we extend the model's original vocabulary by 5000 types, *e.g.*, `<extra_id_x>`. This allows us to have a vocabulary that can encode both text in subword units and speech in DSUs. For the extended vocabulary, we initialize new embeddings from a multivariate Gaussian distribution. The mean of this distribution is set to the average of the original embeddings, while the covariance is derived from the empirical covariance of the original embeddings, scaled by a factor of 1×10^{-5} (Hewitt, 2021).

3.3 SPIREFULL

SPIREFULL is obtained by instruction tuning SPIREBASE on task-specific text and speech data.

3.3.1 Data

We use a mixture of text and speech instructions for ASR, MT, and ST. The prompt formats used during training are shown in Appendix A.2.

Text Data We use TOWERBLOCKS (Alves et al., 2024), which includes high quality translation bitexts between English and the other languages supported by TOWER. It also includes instructions for the translation-related tasks of named entity recognition and automatic post-editing.

ASR Data We use 0.8K hours of ASR data from CommonVoice 18 (CV; Ardila et al., 2020), downsampling strategy as described in Appendix A.1.

ST Data In our IT set, we use 842 hours of speech across three ST training sets: FLEURS (all nine language pairs; we filter out examples whose transcriptions overlap with the FLORES devtest set), Europarl-ST (Iranzo-Sánchez et al., 2020) (en → {de, es, fr, it, nl, pt}), and CoVoST-2 (en→zh). Since this amounts to far less data for ST than ASR, and since en→{ko, ru} have only examples from the tiny FLEURS set, we augment our speech collection with **pseudo-labeled** data, which has been effective for other ST systems (Barrault et al., 2023). We select 300k ASR examples each from CV, SPGI, and GigaSpeech and translate them to all nine target languages using `TowerInstruct-13B`.[7] We then filter examples whose transcript-translation combination has a COMET-QE[8] (Rei et al., 2022b) score under 85. Finally, for each language pair, we sample 60K examples to be used in direct ST prompts and another 60K to be used in multi-turn prompts. This results in 180K direct ST prompts and 180K multi-turn prompts for each language pair.[9] The prompt formats are shown in Appendix A.2.

Dataset	Task	Phase	# DSUs	# Hours
SPGI Speech	ASR	CPT	645M	5.1K
Gigaspeech	ASR	CPT	1.2B	9.9K
MLS	ASR	CPT	2.4B	19.2K
VoxPopuli	ASR	CPT	69M	0.5K
CV	ASR	IT	105M	0.8K
Europarl-ST	ST	IT	122M	1.0K
FLEURS	ST	IT	11M	0.09K
CoVoST-2	ST	IT	12M	0.09K
SPGI Speech	Pseudo-ST	IT	350M	2.8K
GigaSpeech	Pseudo-ST	IT	161M	1.3K
CV	Pseudo-ST	IT	212M	1.7K

Table 1: Statistics for speech training data. Hours are approximated from the number of deduplicated DSUs.

3.3.2 IT Training Setup

We use the `chatml` template (OpenAI, 2023) to format our instructions in dialogue form. We train models using Axolotl[10] on 4 H100-80GB GPUs for 2.7 days. We use a learning rate of 7×10^{-6} and a cosine scheduler with 100 warm-up steps. We train for 4 epochs with an effective batch size of 576 and a weight decay of 0.01. We impose a maximum sequence length of 4096 and use the AdamW optimizer (Loshchilov and Hutter, 2019). Other hyperparameters are derived from TOWERINSTRUCT (Alves et al., 2024).

[7] https://huggingface.co/Unbabel/TowerInstruct-13B-v0.1

[8] https://huggingface.co/Unbabel/wmt22-cometkiwi-da

[9] Due to our aggressive filtering, we were left with slightly fewer examples for en → zh.

[10] https://github.com/axolotl-ai-cloud/axolotl

4 Experiments

We evaluate our models across three tasks: ASR, MT, and ST. First, we present our results for ASR (§4.1), confirming the new capabilities SPIRE has in the speech domain. We then present MT results (§4.2), demonstrating that the speech performance does not come at the expense of the original model's MT performance. Finally, we present results for ST (§4.3) to investigate model performance on a task that requires both ASR and MT capabilities.

Evaluation Setup Across models and tasks, we perform inference with greedy decoding with a maximum of 256 generated tokens. For the TOWER and SPIRE models, we decode with `vllm`. However, since `vllm` does not support all of our baselines, we use alternative libraries (`transformers`) where necessary. Unless specified otherwise, we use zero-shot prompts for all models and tasks.

4.1 ASR

Datasets and Metrics We evaluate ASR performance across multiple test sets, in order to cover a variety of recording styles: Librispeech (LS) test-clean and test-other (Panayotov et al., 2015), FLEURS (Conneau et al., 2023), and VoxPopuli.[11] We report the Word Error Rate (WER) between the hypotheses and gold transcripts, after Whisper normalization (Radford et al., 2023).

Baselines We include the following models:

- **Whisper** (Radford et al., 2023) is an encoder-decoder transformer trained on over 5 million hours of labeled data that performs multilingual ASR and to-English ST. We report results for Whisper-base (74M parameters) and Whisper-large-v3 (1.5B parameters).
- **SeamlessM4T** (Barrault et al., 2023) is an encoder-decoder transformer trained on 406K hours of speech that performs ASR, ST and MT across 100 languages. We report results for SeamlessM4T-large-v2 (2.3B parameters).
- **SALMONN** (Tang et al., 2024) integrates a pre-trained text LLM with separate speech and audio encoders into a single multimodal model.[12] SALMONN uses a LoRA adapter (Hu et al., 2022) to align the spaces.
- **Qwen2-Audio** (Chu et al., 2024) integrates audio into Qwen-7B (Bai et al., 2023) using a specialized encoder that is initialized from Whisper large-v3. The resulting model is pretrained on ∼520K hours of data spanning speech, sound, and music.
- **Spirit-LM** (Nguyen et al., 2025) is a decoder-only model, trained from Llama-2 on 307B tokens of text, 458K hours of unlabeled speech, and 111K hours of labeled speech. As in SPIRE, it uses HuBERT DSUs.
- **HuBERT-large+CTC** is a CTC-based ASR model trained using the same speech representation model we use for DSU generation, and using the same ASR data from the IT stage (Section 3.3.1).[13] Unlike SPIRE, this model has access to a very powerful speech representation backbone, however, lacks strong language modeling capabilities.

	LibriSpeech Clean	LibriSpeech Other	FLEURS	VoxPopuli
Whisper-base	5.0	11.9	12.1	9.8
Whisper-large-v3	1.8	**3.7**	**5.8**	9.2
SeamlessM4T	2.6	4.9	8.1	7.5
SALMONN	2.4	5.3	9.3	8.9
Qwen2-Audio	**1.6**	3.9	6.6	**6.5**
Spirit-LM	*6.0**	*11.0**	-	-
HuBERT-large+CTC	4.3	7.6	11.4	14.7
Our models				
SPIREBASE	28.9	56.3	11.0	13.7
SPIREFULL	4.2	7.1	10.7	15.8

*We were unable to reproduce Spirit-LM's ASR performance; therefore, we report their self-reported LS results using ten-shot prompts.

Table 2: WER on various ASR test sets.

Results Our results are presented in Table 2. SPIREFULL's performance demonstrates that performing both the CPT and IT stages is an effective strategy to give speech capabilities to a text LLM. On the other hand, SPIREBASE does not consistently show reasonable speech performance, however, on FLEURS and VoxPopuli we obtain somewhat strong results in the zero-shot settings, which is surprising given that non-instruction-tuned models often struggle to work out-of-domain without

[11] For CPT models, LS is an in-domain evaluation because its training set is part of MLS.

[12] SALMONN uses 4400 hours of speech/audio data in the IT phase but does not specify the large amount of pre-training ASR and audio captioning data used.

[13] The hyperparameters are described in Appendix B.

	en→xx		xx→en	
	C22	spB	C22	spB
SeamlessM4T	87.22	39.0	87.42	39.9
TOWERBASE-7B	87.38	37.8	88.02	41.7
TOWERINSTRUCT-7B	88.45	38.8	**88.27**	**42.0**
Our models				
SPIREBASE	87.41	37.4	87.97	41.4
SPIREFULL	**88.54**	**39.3**	88.21	41.8

Table 3: COMET-22 (C22) and spBLEU (spB) on the FLORES devtest set between English and the other languages supported by TOWER And SPIRE.

in-context learning examples.[14]

Although SPIREFULL does not match the performance of SeamlessM4T, Whisper-large-v3, SALMONN, or Qwen2-Audio, these were trained on far more speech data than our models (around 10x for Qwen2-Audio and SeamlessM4T). Given this training data gap, it is notable that SPIREFULL *does* outperform Whisper-base on LS and FLEURS, and Spirit-LM on all benchmarks Spirit-LM reports at a fraction of the speech data.

SPIREFULL also outperforms the HuBERT-large+CTC baseline on three out of four datasets—an impressive result given that the CTC model has access to continuous features, which SPIREFULL lacks, showing that our compressed discrete representations *can* recover more powerful features.

4.2 MT

Having demonstrated that our training approach works well to initially equip TOWER with speech processing capabilities, we now turn to MT to investigate whether SPIRE can maintain TOWER's strong performance on MT despite its speech-centric CPT.

Datasets and Metrics We evaluate on two datasets for MT: FLORES-200 (Team et al., 2024), which covers SPIRE's languages, and the WMT23 test set (Kocmi et al., 2023), which covers en↔{de, ru, zh}. We report COMET-22 (COMET; Rei et al., 2022a) and spBLEU[15] (Papineni et al., 2002) scores via the SacreBLEU toolkit (Post, 2018).

Baselines We compare the SPIRE models to the text-to-text translation performance of SeamlessM4T. Additionally, we report the performance of TOWERBASE-7B and TOWERINSTRUCT-7B.

[14]We also tried prompting SPIREBASE with few-shot examples, but the results were much worse, possibly because the length of the DSU sequences led to in-context examples that were too long for the model to handle effectively.

[15]`nrefs:1|case:mixed|eff:no|tok:flores200|smooth:exp|version:2.5.1`

	APE		NER
	en→xx	xx→en	Multilingual
TOWERINSTRUCT-7B	83.08	**80.29**	**71.56**
SPIREFULL	**83.13**	80.08	67.10

Table 4: Results on APE (COMET) and NER (seq. F1).

Results Our results show that even after the speech-centric CPT and mixed speech and text IT stage, the SPIRE models retain the original text-only performance of TOWER on both FLORES (Table 3) and WMT23 (Table 5). This indicates that neither CPT nor IT on speech data negatively impacts the model's ability to perform MT. This is true for both SPIREBASE, which achieves performance comparable to TOWERBASE; and for IT models, where SPIREFULL slightly surpasses the performance of TOWERINSTRUCT on en→xx. SPIREFULL also outperforms SeamlessM4T by both metrics on all WMT23 language pairs, and for both en→xx and xx→en on FLORES.

Translation-related Tasks We follow the evaluation set-up from TOWER (Alves et al., 2024) to additionally evaluate SPIRE on translation-related tasks. In Table 4 we report our results on automatic post-edition (APE) for en↔{de, ru, zh} and named entity recognition (NER) for {de, en, es, fr, it, pt, zh}. SPIRE performs similarly to TOWERINSTRUCT across both tasks and all language directions, maintaining the original text-only capabilities even after training on speech data.

4.3 ST

As SPIRE has shown success at both ASR and MT, we now investigate its performance on ST.

Datasets For ST, we evaluate our models on FLEURS (Conneau et al., 2023), covering ST between all en→xx pairs, and CoVoST-2 (Wang et al., 2021b) for en→{de, zh}. For brevity, we report spBLEU and COMET-22 in Appendix C.

ST approaches As well as direct ST, we report self-cascades, in which each model transcribes the audio before translating its own output to the target language (*i.e.*, ASR followed by MT).

Baselines We compare SPIRE to SeamlessM4T in both direct and cascaded settings. We also report the results of SALMONN and Qwen2-Audio,

	en→de		en→ru		en→zh		de→en		ru→en		zh→en	
	C22	spB	C22	spB	C22	spB	C22	spB	C22	spB	C22	spB
SeamlessM4T	77.76	27.8	83.22	34.2	80.14	29.7	78.69	26.6	80.58	32.5	76.96	23.8
TOWERBASE-7B	79.96	36.1	83.08	34.2	83.49	33.3	83.56	41.1	80.06	32.7	78.48	23.5
TOWERINSTRUCT-7B	82.34	38.8	**84.66**	**34.9**	85.09	35.3	84.95	45.1	**82.94**	**36.7**	**80.14**	26.1
Our models												
SPIREBASE	79.88	34.7	83.04	33.7	83.85	32.4	83.19	40.5	80.20	32.4	78.65	23.1
SPIREFULL	**82.50**	**39.5**	84.60	**34.9**	**85.37**	**37.3**	**85.24**	**45.2**	82.58	36.4	79.92	**26.3**

Table 5: COMET-22 (C22) and spBLEU (spB) on the WMT23 test set.

which are both 7B parameter models, like SPIRE. However, SALMONN and Qwen2-Audio do not support text-to-text translation, so we use them only for direct ST.[16] There are also coverage differences between the models: while SeamlessM4T can handle all of SPIRE's language pairs, neither SALMONN nor Qwen2-Audio supports en→ko; SALMONN also does not support en→ru.

Results Our FLEURS ST results are reported in Table 7. SeamlessM4T performs best at direct ST for all language pairs except en→zh. Among the 7B parameter models, SPIREFULL is the best direct model on average, notably beating SALMONN on all language pairs except en→zh. It also outperforms Qwen2-Audio on 6 out of 8 language pairs that Qwen2-Audio supports, and ties or beats it for all except en→zh and en→de.

Performance on CoVoST-2 (Table 6) tells a different story. Although SPIREFULL maintains its advantage over SeamlessM4T in self-cascaded translation, it attains the worst performance on en→zh, while performing similarly to SALMONN for en→de. This shows that the direct ST performance of SPIREFULL is dataset-dependent, which could be a consequence of its relatively small training data.

SPIREFULL achieves the best self-cascaded performance by a significant margin for both datasets, outperforming SeamlessM4T by a large margin in this setting. This demonstrates that SPIREFULL maintains greater robustness to its own outputs than SeamlessM4T, supporting the insight that LLM-based translation models can be very robust to perturbations (Peters and Martins, 2025).

[16] Although Whisper is frequently used for ST, we exclude it because it only supports to-English translation, whereas SPIRE is a from-English ST model. Therefore ST comparisons between the two models are impossible.

	en→de		en→zh	
	C22	spB	C22	spB
Self-cascade				
SeamlessM4T	72.40	21.7	72.32	17.0
SPIREFULL	78.05	31.8	79.50	28.1
Direct				
SALMONN	74.98	22.7	80.92	27.8
Qwen2-Audio	82.29	34.5	85.27	38.7
SeamlessM4T	85.95	42.3	83.62	31.3
SPIREFULL	73.96	25.4	74.53	21.0

Table 6: ST results on CoVoST-2.

5 Analysis

The key innovation of our approach is the application of the CPT followed by IT paradigm to discretized speech allowing us to build upon existing text-only capabilities of our base model. Here, we analyze how the composition of these two training phases contributes overall to model performance across all tasks previously evaluated. To that end, we consider several variants of SPIREBASE and SPIREFULL which are described in Table 8 and whose results are reported in Table 9.

- *i*) no CPT was performed and IT was performed with the entire IT data mix (TOWERFULL);
- *ii*) CPT was performed and no data from TOWERBLOCKS was seen during IT (SPIRENOBLOCKS), and
- *iii*) CPT was performed and pseudo-labeled ST data and FLEURS were omitted from the IT data mix (SPIRENOPSEUDO).

We report additional datasets in Appendix D.

Effectiveness of CPT and IT Our previous results demonstrated that using both CPT and IT was the most effective strategy. The performance

	de	es	fr	it	ko	nl	pt	ru	zh	avg_7	avg_{all}
Self-Cascade											
SeamlessM4T	24.2	21.5	37.7	18.9	12.5	16.9	28.2	27.1	14.6	23.1	22.4
SPIREFULL	**38.1**	**29.4**	**45.3**	**31.2**	**23.1**	**31.2**	**42.9**	**33.5**	**29.0**	**35.3**	**33.7**
Direct											
SeamlessM4T	**39.2**	**28.0**	**48.1**	**30.6**	**21.5**	**30.8**	**47.5**	**34.3**	23.2	**35.3**	**33.7**
SALMONN	25.5	20.8	34.3	16.7	0.1	20.5	32.6	3.1	21.9	24.6	19.5
Qwen2-Audio	31.8	23.5	31.3	23.5	5.4	22.3	36.1	23.7	**24.7**	27.6	24.7
SPIREFULL	31.1	23.5	37.9	25.5	15.4	25.7	37.3	26.9	21.0	28.9	27.1

Table 7: FLEURS ST ex→xx results with self-cascade and direct models in terms of spBLEU. avg_7 covers the 7 language pairs that all models in the table support (excluding en→{ko, ru}).

Model	Base Model	CPT		IT		
		Speech	Text	Speech	Pseudo	Text
TOWERFULL	TowerBase-7B	✗	✗	✓	✓	✓
SPIREBASE	SpireBase	✓	✓	✗	✗	✗
SPIREFULL	SpireBase	✓	✓	✓	✓	✓
SPIRE *Variants*						
SPIRENOBLOCKS	SpireBase	✓	✓	✓	✓	✗
SPIRENOPSEUDO	SpireBase	✓	✓	✓	✗	✓

Table 8: Ablations of our models. The CPT and IT columns indicate which data was seen during training.

	ASR	**MT**				**ST**	
		en→xx		xx→en		en→xx	
	WER	C22	spB	C22	spB	C22	spB
SPIREFULL	4.2	88.54	39.3	88.21	41.8	**81.33**	**27.1**
TOWERFULL	9.5	**88.57**	**39.4**	88.17	41.7	79.10	26.1
SPIRENOBLOCKS	4.1	82.98	34.2	85.93	36.1	81.11	27.1
SPIRENOPSEUDO	**3.9**	88.40	38.9	**88.22**	**42.0**	62.80	27.1

Table 9: Ablation models and SPIREFULL on LS Clean for ASR, FLORES devtest for MT, and Fleurs for ST reporting WER, COMET-22 (C22), and spBLEU (spB).

gap between SPIREFULL and the TOWERFULL on ASR (5.3 points in LS test-clean) further shows that IT alone is also not as effective. However, for ST we observe that only performing IT leads to a strong model that is capable of performing speech translation unlike SPIREBASE where we also attempted direct ST but the model failed to produce output in the target language, even when given few-shot prompts. Despite the impressive results from TOWERFULL, we still observe the best performance by SPIREFULL showing that while the effect of CPT is not as drastic as in the case of ASR, we still observe gains with a speech-centric CPT phase.

Modality Interplay Our results show that text and speech modalities are orthogonal to each other. Specifically, the performances of TOWERFULL and SPIREFULL show that speech-centric CPT *does not* degrade the text performance of the base model. However, MT quality suffers when TOWERBLOCKS is removed from the IT data, as is shown by SPIRENOBLOCKS's much weaker performance than SPIREFULL. Simultaneously, SPIREFULL performs on par with SPIRENOBLOCKS on both ASR and ST, indicating that adding text instructions also *does not* degrade performance on speech tasks. It is worth highlighting that a model strong at both MT and ASR (SPIRENOPSEUDO) does not lead to a strong ST model, showing surprisingly that competence at MT is not very helpful for direct ST.

6 Conclusion

In this work we presented SPIRE, a simple and effective recipe for adapting a text-based, translation-specialist LLM to the speech modality while preserving the original performance on text-based tasks. We investigated the impact of speech integration on two stages of LLM adaptation, CPT and IT, finding that both contribute to the final model's performance on speech tasks. Our results demonstrate that we are able to successfully integrate a new modality without compromising the original model's capabilities. SPIRE achieves competitive performance on ASR, while its MT abilities remain on par with the original TOWER model. Finally, for the ST task, we find that the leveraging ASR and MT data does not directly transfer to ST performance. Nonetheless, the model achieves promising performance with both direct and self-cascaded ST.

As future work, we intend to extend this recipe to multilingual settings by replacing our English HuBERT speech component by the multilingual mHuBERT-147 (Boito et al., 2024). To benefit the community, we only use publicly available and licensed data to train our models, making our results reproducible.

Limitations

The downstream tasks we evaluate on are restricted to MT and ASR/ST, which provides an idea of the model performance but do not give us the full picture. We plan to address this by utilizing the LM-harness evaluation (Gao et al., 2024) to evaluate on a suite of text-based benchmarks such as MMLU (Multitask Language Understanding) (Hendrycks et al., 2021b,a), Arc (Commonsense Reasoning) (Clark et al., 2018), Belebele (Reading Comprehension) (Bandarkar et al., 2024), and HellaSwag (Sentence Completion) (Zellers et al., 2019). Lastly, our model handles speech and text on the input side but is currently limited to generating only text.

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A Data

A.1 Speech Data Preprocessing

Normalization In order to make transcripts consistent across the different datasets, the following normalization is applied:

- **GigaSpeech (CPT):** we lower-case the text and replace punctuation tags: <COMMA>, <PERIOD>, QUESTIONMARK>, <EXCLAMATIONPOINT> with their appropriate punctuation.
- **MLS (CPT):** we apply a tail-end normalization step here which uniformly samples each speaker to have at maximum 13 transcriptions. This allows us to have a better distribution of speakers.
- **CV (IT):** we subsampled from CommonVoice to ensure a minimum duration of 3 seconds per sample. To enhance transcript diversity, we limit each transcript to 4 unique speakers.

Deduplication As in previous work (Zhang et al., 2023; Rubenstein et al., 2023; Chang et al., 2024), we merge consecutive repeated DSU tokens into a single token to reduce sequence length.

A.2 Prompt Format

Table 10 show the prompts used during both training stages.

ASR (CPT)
Speech:<extra_id_i>···<extra_id_j> English: {TRANSCRIPT}
MT (CPT)
Source_lang: Source-sentence Target_lang: {TRANSLATION}
ASR (IT)
Speech: <extra_id_i>···<extra_id_j> English: {TRANSCRIPT}
Direct ST (IT)
Speech: <extra_id_i>···<extra_id_j> TARGET_LANG: {TRANSLATION}
Multi-turn ST (IT)
Speech: <extra_id_i>···<extra_id_j> English:{TRANSCRIPT} TARGET_LANG: {TRANSLATION}

Table 10: Prompt formats for CPT and IT.

B CTC-based ASR model

We train a CTC-based ASR model using the HuggingFace Transformers library (Wolf, 2019), leveraging the ASR data from the IT stage (CommonVoice, Table 1) as training data. Our ASR model is made of the HuBERT-Large[17] speech representation model, followed by three hidden layers and a vocabulary projection layer. We train for 50 epochs with a dropout of 0.3 and a learning rate of 1e-4 with a warm-up ratio of 0.15. The best checkpoint is selected using CER scores. This was obtained at step 220K (at epoch 12.8).

C ST results

Table 11 report results of ST on FLEURS across baseline models and SPIREFULL. We report COMET-22. We observe the same trend in scores as reported by spBLEU where in SPIREFULL obtains the best self-cascaded performance while beating Qwen2-Audio and SALMONN on direct ST across most language pairs. SeamlessM4T obtains the overall best performance in direct ST.

D Ablation results

Table 12 reports results from all remaining evaluation datasets across ASR, MT, and ST. We report the same metrics as in Section 4. Here as well, we note that in MT, the inclusion of speech data did not degrade text-only performance (SPIREFULL vs. TOWERFULL). Similarly, the inclusion of task-specific text data also did not harm performance on ASR (SPIRENOBLOCKS vs. SPIREFULL). Lastly, SPIREFULL has the best performing direct ST system, further showing that individual task competencies (in MT and ASR) do not contribute directly to a compositional task (ST) but rather the inclusion of task-specific data leads to the highest gains (SPIRENOPSEUDO vs SPIREFULL).

[17] https://huggingface.co/facebook/hubert-large-ll60k

	de	es	fr	it	ko	nl	pt	ru	zh	avg_7	avg_{all}
Self-Cascade											
SeamlessM4T	72.69	76.97	78.06	76.03	75.33	72.58	78.25	79.38	69.76	74.91	75.45
SPIREFULL	**84.26**	**83.32**	**84.70**	**85.16**	**86.89**	**84.91**	**86.01**	**86.45**	**85.21**	**84.80**	**85.21**
Direct											
SeamlessM4T	**84.79**	**83.20**	**85.32**	**85.03**	**85.17**	**85.17**	**86.75**	**86.31**	79.90	**84.31**	**84.63**
SALMONN	77.41	77.99	79.95	74.47	61.07	77.18	80.94	53.05	**81.63**	78.51	73.74
Qwen2-Audio	79.82	80.43	79.44	81.28	69.33	78.75	83.41	77.90	80.71	80.55	79.01
SPIREFULL	80.16	79.82	80.68	81.63	82.62	81.93	83.18	82.19	79.76	81.02	81.33

Table 11: FLEURS ST ex→xx results with self-cascade and direct models in terms of COMET-22. avg_7 covers the 7 language pairs that all models in the table support (excluding en→{ko, ru}).

	ASR			**MT**				**ST**	
	WER			C22	spB	C22	spB	C22	spB
	LS Other	Fleurs	VoxPopuli	en→xx		xx→en		en→xx	
SPIREFULL	**7.1**	10.7	15.8	84.16	**37.2**	**82.58**	**41.8**	**81.33**	**27.1**
TOWERFULL	13.8	14.3	40.7	**84.19**	36.9	82.25	35.6	71.52	20.1
SPIRENOBLOCKS	7.4	**10.4**	15.8	73.12	26.9	74.78	25.1	74.02	23.2
SPIRENOPSEUDO	7.3	11.1	**14.3**	83.93	36.9	82.50	35.9	59.88	6.8

Table 12: Ablation models and SPIREFULL on LS Other, Fleur, VoxPopuli for ASR, WMT23 for MT, and CoVoST-2 for ST reporting WER, COMET-22 (C22), and spBLEU (spB).