

RosettaSpeech: Zero-Shot Speech-to-Speech Translation from Monolingual Data

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Abstract

The scarcity of parallel speech corpora critically hampers speech-to-speech translation (S2ST), often forcing reliance on complex, multi-stage pipelines. This paper introduces RosettaSpeech, a novel and simplified framework for zero-shot S2ST that is trained on monolingual speech-text data augmented by machine translation supervision. While our method leverages the linguistic knowledge inherent in text-based NMT models, it strictly eliminates the need for parallel speech-to-speech pairs. Our model uniquely uses text as an intermediate bridge during training but functions as a direct, end-to-end speech-to-speech model at inference. This streamlined approach achieves state-of-the-art results on standard benchmarks. For instance, on the CVSS-C test set, RosettaSpeech outperforms leading systems, achieving an ASR-BLEU score of 25.17 for German-to-English and 29.86 for Spanish-to-English—relative gains of over 27% and 14%, respectively. Furthermore, we demonstrate that a single model can deliver strong many-to-one translation performance (FR/ES/DE → EN). We also provide a foundational analysis of how training data scaling impacts model performance. By prioritizing reliance on abundant parallel text rather than difficult-to-acquire parallel speech, RosettaSpeech offers a scalable path to creating high-quality, speaker-preserving S2ST for a much broader array of languages.

1 Introduction

Speech-to-speech translation (S2ST) stands as a pivotal technology for dismantling language barriers, enabling seamless and natural communication across the globe. The ultimate goal is to create systems that can not only accurately translate spoken content but also preserve the rich paralinguistic

information of the original speaker—such as tone, emotion, and prosody—in real-time.

Conventional approaches tackle this challenge with cascaded systems, which chain together separate Automatic Speech Recognition (ASR), Machine Translation (MT), and Text-to-Speech (TTS) models (Nakamura et al., 2006; Wahlster, 2013). While this modular design benefits from leveraging highly optimized, pre-trained components, it suffers from critical limitations, including error propagation, significant latency, and a fundamental inability to transfer prosodic information.

To address these issues, end-to-end (E2E) models have emerged, offering a direct mapping from source to target speech within a single neural network (Jia et al., 2019, 2022a; Zhang et al., 2024). These E2E systems can mitigate latency but struggle to effectively preserve the source speaker’s voice, and their development is severely hampered by a data bottleneck: they require massive, parallel speech-to-speech translation (S2ST) corpora, which are prohibitively expensive and exist for only a handful of high-resource languages. Recent efforts in unsupervised S2ST have sought to overcome this data scarcity by using only monolingual data. However, these methods often rely on complex, multi-stage training pipelines, pseudo-labeling from cascaded models (Wang et al., 2022), or specialized architectures that can be difficult to train and scale (Barrault et al., 2023; Fang et al., 2024b; Nachmani et al., 2024).

In this work, we introduce RosettaSpeech, a novel and simplified framework for zero-shot¹ speech-to-speech translation. Unlike prior works that rely on complex pipelines, our approach bridges the modality gap by leveraging off-the-shelf NMT models to transform abundant monolingual speech-text pairs into synthetic S2ST train-

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¹We define “zero-shot” in this context as the complete absence of parallel *source-speech* to *target-speech* data.

ing targets. Although this implies a dependency on text-based translation resources, it successfully circumvents the critical bottleneck of acquiring expensive parallel speech corpora.

Crucially, RosettaSpeech is designed to address the "*asymmetric resource*" scenario prevalent in many world languages. While thousands of languages have achieved a "text digitization milestone"—possessing decent text translation models or bitexts—they lack the massive parallel speech data required for conventional S2ST. By decoupling the need for speech parallelism from linguistic supervision, our framework offers a scalable path to unlock high-quality, speaker-preserving S2ST for this broad array of "*text-rich, speech-poor*" languages.

Our primary contributions are as follows:

1. We propose RosettaSpeech, a novel and highly effective framework for end-to-end S2ST that simplifies complex, multi-stage pipelines into a robust, single-stage process, achieving state-of-the-art results on standard benchmarks without requiring any *parallel speech-to-speech corpora*.
2. We demonstrate that a single model can be trained to perform many-to-one translation (e.g., French/Spanish/German to English) and achieve exceptional performance.
3. We provide a foundational analysis of how training data and steps affect model performance, providing a crucial empirical foundation for future work on scaling S2ST systems to even larger models and more languages.

By demonstrating that high-quality, speaker-preserving S2ST is achievable without parallel speech corpora, RosettaSpeech paves the way for developing powerful translation systems for a much wider and more diverse set of the world’s languages.

2 Related Work

2.1 Cascaded Speech Translation

Conventional approaches to Speech-to-Speech Translation (S2ST) employ a cascaded architecture, decomposing the task into a sequence of three independently optimized modules (Jain et al., 1991; Nakamura et al., 2006; Wahlster, 2013): 1) Automatic Speech Recognition (ASR) to convert source speech to text, 2) Machine Translation (MT) to

translate the source text to the target language, and 3) Text-to-Speech (TTS) synthesis to generate the final audio output.

$$\text{Speech}_{\text{src}} \xrightarrow{\text{ASR}} \text{Text}_{\text{src}} \xrightarrow{\text{MT}} \text{Text}_{\text{tgt}} \xrightarrow{\text{TTS}} \text{Speech}_{\text{tgt}}$$

The primary advantage of this modular design is its simplicity and the ability to leverage powerful, pre-trained models for each sub-task. Each component can be developed and improved independently. However, this pipeline architecture introduces several critical limitations. A principal issue is *error propagation*, where inaccuracies from the ASR model are passed to and often amplified by the subsequent MT component, degrading the final translation quality. Furthermore, the sequential processing of the three stages inherently introduces significant latency, rendering the system unsuitable for real-time communication. Perhaps most critically, the reliance on an intermediate text representation severs the transfer of *paralinguistic information*—such as prosody, emotion, and speaker identity—from the source speech. This results in synthesized output that lacks the naturalness and expressiveness of the original speaker. While some studies (Bahar et al., 2019; Wang et al., 2020) show that highly optimized cascaded systems can achieve competitive translation accuracy, they fundamentally struggle to overcome the challenges of high latency and the loss of prosodic fidelity.

2.2 End-to-End Speech Translation

2.2.1 Supervised

To overcome the inherent limitations of cascaded systems, research has increasingly shifted towards end-to-end (E2E) models (Jia et al., 2019, 2022a; Barrault et al., 2023). These models are designed to perform direct speech-to-speech translation within a single, jointly optimized neural network. By unifying the process, E2E systems can theoretically eliminate the latency introduced by sequential processing and mitigate the problem of error propagation. More importantly, this direct mapping from source to target speech allows for the preservation of paralinguistic information, enabling the translated audio to retain the prosody, emotion, and vocal characteristics of the original speaker.

Despite their conceptual advantages, the widespread adoption of supervised E2E models is severely constrained by a critical bottleneck: the scarcity of parallel S2ST data. Training these large, data-hungry networks requires extensive corpora where the same utterance is available in both

the source and target languages, often spoken by the same individual to maintain vocal consistency. Creating such datasets is exceptionally expensive and time-consuming, meaning they exist for only a handful of high-resource language pairs. This fundamental data dependency remains the primary obstacle to scaling E2E solutions to the vast majority of the world’s languages.

2.2.2 Unsupervised

To overcome the scarcity of parallel data, unsupervised speech-to-speech translation (S2ST) leverages monolingual resources through innovative methods. Strategies range from creating pseudo-labels by cascading unsupervised ASR, MT, and TTS systems (Wang et al., 2022), to training direct end-to-end models like Translatotron 3 (Nachmani et al., 2024), which uses back-translation and unsupervised embedding mapping. Further advancements focus on specific capabilities like expressivity and modularity. SONAR EXPRES-SIVE (Duquenne et al., 2023) disentangles semantic content from a separately learned prosody embedding to enable zero-shot expressive translation, while ComSpeech (Fang et al., 2024b) introduces a composite framework with a vocabulary adaptor and contrastive learning to combine arbitrary pretrained S2TT and TTS models, achieving high-quality S2ST without any parallel speech data. However, these methods often rely on complex, multi-stage pipelines or specialized model architectures, which can be difficult to train and scale effectively across many languages.

2.3 Omni-Language Models

Omni-Language Models (Xie and Wu, 2024; Fang et al., 2024a; Chen et al., 2024; Défossez et al., 2024) are naturally suited for speech-to-speech related tasks. However, they are often trained on specialized and expensive data like speech-based question-answering (QA) corpora, which limits scalability. RosettaSpeech bypasses this bottleneck by training exclusively on abundant, monolingual speech-text pairs, requiring no parallel S2S or QA data. This data-efficient approach simplifies the training pipeline and makes it feasible to build S2ST systems for a much wider range of languages.

3 Methodology

3.1 Datasets

A core challenge in developing robust speech-to-speech translation (S2ST) systems is the profound

scarcity of true parallel corpora, which contain the same utterance spoken in both a source and target language. Acquiring such data is prohibitively expensive and labor-intensive.

Our methodology addresses this by explicitly decoupling speech supervision from translation supervision. We prioritize reliance on NMT over TTS-dependent pipelines for a strategic reason: parallel text data is orders of magnitude more abundant and accessible than the high-fidelity, studio-grade speech corpora required to train robust TTS systems. By utilizing NMT to generate pseudo-parallel targets, we effectively trade the difficult constraint of acquiring paired speech for the much looser constraint of acquiring parallel text.

The construction process involves two primary workflows, depending on the language of the monolingual source data:

1. **From Source Language Data:** For a given monolingual corpus in the source language, which provides (S_{src}, T_{src}) pairs, we use a high-quality neural machine translation (NMT) model² (Kudugunta et al., 2023) to translate the source text T_{src} into the target language, creating T_{tgt} . This procedure yields a pseudo-parallel triplet of $(S_{src}, T_{src}, T_{tgt}^*)$.
2. **From Target Language Data:** Conversely, for a monolingual corpus in the target language providing (S_{tgt}, T_{tgt}) pairs, we apply the same NMT model in the reverse direction to translate T_{tgt} into T_{src} . This results in a corresponding triplet formatted as $(T_{src}^*, T_{tgt}, S_{tgt})$.

Our strategy repurposes a diverse set of existing datasets to create a pseudo-parallel corpus. To ensure its quality and fidelity, we apply a rigorous filtering process. After generating translations, we use the COMET (Rei et al., 2020) metric to score the quality of each source-target T_{src} - T_{tgt} pair. Only pairs that meet or exceed a predefined threshold (e.g., 0.80 for EN \leftrightarrow DE) are retained for training. This quality control mechanism is critical, as it prevents the model from learning from inaccurate translations and thereby enhances the final system’s performance and reliability. The resulting curated corpus provides the structured data needed to train our model to map from a source modality (speech or text) to target text and speech tokens, all

²<https://huggingface.co/google/madlad400-3b-mt>

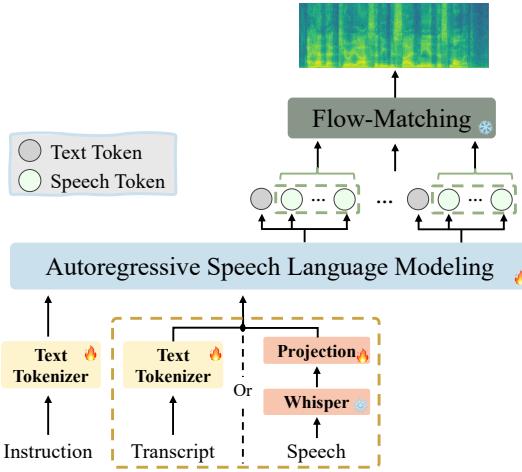


Figure 1: The training architecture of RosettaSpeech, where the components enclosed in dashed boxes are optional depending on the training sample.

without requiring direct (S_{src}, S_{tgt}) parallel examples.

3.2 Architecture

As shown in Figure 1, the architecture of RosettaSpeech is designed to process source speech to generate translated text and speech. This section details the model’s core components: speech modeling, the LLM backbone, and the multi-head projection layers.

3.2.1 Speech Modeling

Our approach processes input speech using the encoder from Whisper-medium (Radford et al., 2023). It transforms the raw 16kHz audio waveform into a sequence of continuous hidden-state vectors. These vectors are generated at a rate of 50 Hz and encapsulate rich acoustic and phonetic features of the source speech. For the output, the target speech waveform is converted into a sequence of discrete semantic tokens using the speech tokenizer from CosyVoice2 (Du et al., 2024). This tokenized representation enables the LLM to generate speech autoregressively by predicting the next token in the sequence.

3.2.2 Backbone

The core of our architecture is the Qwen3-0.6B Large Language Model (LLM) (Yang et al., 2025), which functions as the central engine for all translation tasks. The selection of this model was primarily motivated by its advanced capabilities in text understanding. Critically, its inherent multilingual proficiency is essential for the cross-lingual

objectives of our work. By leveraging a pre-trained LLM as the backbone, RosettaSpeech inherits the extensive world knowledge and complex linguistic patterns acquired during the LLM’s foundational training, thereby providing a robust starting point for our specialized translation tasks.

3.2.3 Multi-Head Projection

To enable the model to generate both text and speech outputs, we employ a multi-head projection mechanism on top of the LLM backbone (Xie and Wu, 2024; Chen et al., 2024). The final hidden-state representations from the LLM are passed to separate linear projection heads for each modality:

- A text projection head maps the hidden states to the vocabulary of the text tokenizer. This head is responsible for predicting the target text translation.
- A set of speech projection heads maps the same hidden states to the vocabularies of the discrete speech tokenizer’s codebooks. These heads work in concert to predict the sequence of semantic tokens required for synthesizing the target speech.

This multi-head design allows the model to be trained jointly on both text and speech generation tasks, learning to produce aligned outputs in both modalities from a shared latent representation.

3.3 Training

The model is trained following the procedure detailed in Algorithm 1. The training process alternates between two distinct tasks based on the data sampled in each iteration:

1. **Speech-to-Text Translation (S2TT):** This branch utilizes a monolingual source corpus (S_{src}, T_{src}) . The model is fed the speech input S_{src} and is trained to generate its text translation, while the original transcript T_{src} is disregarded. To supervise the training, we compute the loss against a pseudo-target translation T_{tgt}^* generated by an NMT system. Consequently, only the model’s text output is used, and any generated speech is discarded.
2. **Text-to-Speech Translation (T2ST):** For data from the target language monolingual corpus (S_{tgt}, T_{tgt}) , we use the NMT-generated pseudo-source text T_{src}^* as input. The model

is then trained to produce both the ground-truth target text T_{tgt} and the ground-truth target speech S_{tgt} . The loss is calculated for both modalities.

For both text and speech generation, the training objective is to minimize the standard cross-entropy loss between the model’s predictions and the target sequences. The total loss for a given training batch is the sum of the S2TT and T2ST losses:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{S2TT}} + \mathcal{L}_{\text{T2ST}}$$

where each loss term is defined as:

$$\mathcal{L} = - \sum_{i=1}^N \log P(y_i | y_{<i}, X; \theta)$$

Here, X is the input sequence, y_i is the i -th token of the target sequence (either text or discrete speech tokens), and θ represents the model parameters. This joint training approach enables the model to learn mappings from both speech and text modalities to a shared latent space that can produce aligned text and speech outputs.

3.4 Inference

Although the model has never been exposed to any paired source and target speech data ($S_{\text{src}}, S_{\text{tgt}}$) during training, it can perform direct speech-to-speech translation at inference time. The model takes the source speech waveform, S_{src} , as input and autoregressively generates both the translated text, T_{tgt} , and the translated semantic speech tokens, S_{tgt} , in a single forward pass. We then employ an off-the-shelf conditional flow matching (CFM) model (Du et al., 2024) to convert these semantic tokens into mel-spectrograms. Crucially, this stage allows for effective control over the speaker identity and paralinguistic information in the synthesized audio by conditioning the generation on a given speech prompt. Finally, the mel-spectrograms are synthesized into the output waveform using a HiFi-GAN vocoder (Kong et al., 2020).

4 Experiments

4.1 Datasets

We validate our method on speech-to-speech translation for three language pairs: French to English (FR→EN), German to English (DE→EN), and Spanish to English (ES→EN). The training data is constructed entirely from monolingual corpora,

Algorithm 1 Pipeline of RosettaSpeech

Require: [I] Monolingual source corpus \mathcal{D}_{src} and target corpus \mathcal{D}_{tgt} [II] Pre-trained neural machine translation models $\text{NMT}_{\text{src} \rightarrow \text{tgt}}$ and $\text{NMT}_{\text{tgt} \rightarrow \text{src}}$

Ensure: A model f_{θ} for direct and zero-shot speech-to-speech translation $S_{\text{src}} \rightarrow S_{\text{tgt}}$

Training

- 1: **for** each training iteration **do**
- // 1. Speech-to-Text Translation (S2TT)
- 2: Sample $(S_{\text{src}}, T_{\text{src}})$ from \mathcal{D}_{src}
- 3: $T_{\text{tgt}}^* \leftarrow \text{NMT}_{\text{src} \rightarrow \text{tgt}}(T_{\text{src}})$
- 4: $\hat{T}_{\text{tgt}, -} \leftarrow f_{\theta}(S_{\text{src}})$
- 5: $\mathcal{L}_{\text{S2TT}} \leftarrow \text{Loss}(\hat{T}_{\text{tgt}}, T_{\text{tgt}}^*)$
- // 2. Text-to-Speech Translation (T2ST)
- 6: Sample $(S_{\text{tgt}}, T_{\text{tgt}})$ from \mathcal{D}_{tgt}
- 7: $T_{\text{src}}^* \leftarrow \text{NMT}_{\text{tgt} \rightarrow \text{src}}(T_{\text{tgt}})$
- 8: $\hat{T}_{\text{tgt}}, \hat{S}_{\text{tgt}} \leftarrow f_{\theta}(T_{\text{src}}^*)$
- 9: $\mathcal{L}_{\text{T2ST}} \leftarrow \text{Loss}(\hat{T}_{\text{tgt}}, T_{\text{tgt}}) + \text{Loss}(\hat{S}_{\text{tgt}}, S_{\text{tgt}})$
- // 3. Parameter Update
- 10: $\mathcal{L}_{\text{total}} \leftarrow \mathcal{L}_{\text{S2TT}} + \mathcal{L}_{\text{T2ST}}$
- 11: Update θ using $\nabla_{\theta} \mathcal{L}_{\text{total}}$
- 12: **end for**

Inference

return $(T_{\text{tgt}}, S_{\text{tgt}}) = f_{\theta}(S_{\text{src}})$

without relying on any parallel speech-to-speech data. For the target language, *English*, we utilize speech-text pairs from the Gigaspeech (Chen et al., 2021) and the English portion of the Multilingual LibriSpeech (MLS) (Pratap et al., 2020) datasets. For the source languages—*French*, *German*, and *Spanish*—we use the corresponding language-specific subsets from the VoxPopuli (Wang et al., 2021) and Multilingual LibriSpeech corpora. These monolingual datasets form the basis from which we generate the pseudo-parallel data required for training, as detailed in the preceding section.

4.2 Implementation Details

4.2.1 Training

For our model, we use CosyVoice2’s speech tokenizer, which has a single-layer, 6561-entry codebook and operates at 25 Hz for 16kHz speech. The outputs from the final Transformer layer of the

Models	FR → EN		ES → EN		DE → EN	
	BLEU (↑)	ASR-BLEU (↑)	BLEU (↑)	ASR-BLEU (↑)	BLEU (↑)	ASR-BLEU (↑)
Ground Truth	-	84.52	-	88.54	-	75.53
Qwen3-0.6B (Yang et al., 2025)	32.68	-	34.35	-	27.42	-
Zero-Shot						
ComSpeech (Fang et al., 2024b)	30.72	28.15	26.51	24.80	19.41	18.16
Ours (Unparalleled)	31.78	27.86	32.64	29.86	31.95	25.17
Non Zero-Shot						
Translatotron (Jia et al., 2019)	-	16.96	-	8.72	-	1.97
Translatotron 2 (Jia et al., 2022a)	28.82	25.49 (26.07)	25.82	22.35 (22.93)	18.66	16.24 (16.91)
S2UT (Lee et al., 2021)	-	20.91 (22.23)	-	16.94 (18.53)	-	2.46 (2.99)
UnitY (Inaguma et al., 2022)	-	26.90 (27.77)	-	23.93 (24.95)	-	18.19 (18.74)
DASpeech (Fang et al., 2023)	-	25.03	-	21.37	-	16.14
StreamSpeech (Zhang et al., 2024)	31.59 (32.60)	27.58 (28.45)	28.97 (30.35)	26.16 (27.25)	21.96 (23.36)	19.72 (20.93)
Hibiki (Labiausse et al., 2025)	-	30.5	-	-	-	-
Ours (Paralleled, Scratch)	24.16	15.32	23.62	9.38	17.71	9.02
Ours (Paralleled, Fine-tuned)	32.88	31.56	35.23	33.05	32.62	29.90
Ours (Paralleled, Fine-tuned) [†]	33.11	32.16	30.92	29.35	23.22	21.54

[†]Indicates a single model for all three language pairs. Other results correspond to models trained for each language pair individually.

Table 1: Speech-to-speech translation performance on the CVSS-C test set for FR/ES/DE→EN. We reorganize results into two blocks: **Zero-shot** (ComSpeech, RosettaSpeech (Unparalleled)) and **Non zero-shot** (all others). Setup follows StreamSpeech. Results without parentheses are from greedy search, while those in parentheses are from beam search (beam size 10).

Qwen model are then projected into five distinct linear layers: one for text tokens and the remaining four for speech tokens. The same configuration was used for training the model for each language pair. We employed the AdamW optimizer with a learning rate of 2×10^{-3} , $\beta_1 = 0.9$, $\beta_2 = 0.999$, an epsilon of 1×10^{-6} , and a weight decay of 0.01. A learning rate scheduler is utilized, featuring a linear warm-up for the initial 10K steps, followed by a linear decay for the remainder of the 100K total training steps. Gradient accumulation is performed over micro-batches. The training of each model was done on 8 NVIDIA A100 40GB GPUs.

4.2.2 Inference

During inference, we use distinct decoding strategies for the generation of text and speech tokens. For the text translation, we utilize greedy search, which we found empirically to yield higher-quality results than nucleus sampling for this task. Conversely, for the generation of discrete speech tokens, we use nucleus sampling with a TopK of 20, a TopP of 0.8, and a temperature of 0.95. Furthermore, we apply a length penalty during speech generation to prevent the model from producing repetitive or non-terminating audio outputs.

4.3 Evaluation

To ensure a fair comparison, we adopt the evaluation setting of StreamSpeech (Zhang et al., 2024) and assess our model on the CVSS-C (Jia et al., 2022b) test set for French, German, and Spanish to English speech-to-speech translation (FR/DE/ES→EN). We measure performance using two key metrics: the BLEU score for the translated text and the ASR-BLEU score for the synthesized speech. The ASR-BLEU score is calculated by first transcribing the generated audio with a pre-trained ASR model (Baevski et al., 2020) and then computing the SacreBLEU (Post, 2018) score against the reference text. We compare RosettaSpeech against several state-of-the-art S2ST models, including Translatotron (Jia et al., 2019), Translatotron 2 (Jia et al., 2022a), S2UT (Lee et al., 2021), UnitY (Inaguma et al., 2022), DASpeech (Fang et al., 2023), ComSpeech (Fang et al., 2024b), StreamSpeech (Zhang et al., 2024), and Hibiki (Labiausse et al., 2025).

4.4 Results

Translation Quality As presented in Table 1, our RosettaSpeech model, trained exclusively on monolingual data, establishes a new state-of-the-art for zero-shot speech-to-speech translation on the CVSS-C benchmark. It significantly outperforms prior systems, even those trained with paral-

lel speech data.

For French-to-English translation, our model achieves a highly competitive ASR-BLEU score of 27.86 and a BLEU score of 31.78, surpassing strong baselines like StreamSpeech (Zhang et al., 2024). While Hibiki (Labiausse et al., 2025) reports a higher ASR-BLEU, it’s crucial to note that it was trained on a massive paired dataset, larger in volume than our unparalleled data.

In the Spanish-to-English task, RosettaSpeech establishes a new benchmark with an ASR-BLEU of 29.86, marking a relative improvement of over 14% against the previous leading system. This is complemented by a top-tier text BLEU score of 32.64, demonstrating excellent accuracy. The performance gains are most pronounced for German-to-English, where our model achieves an ASR-BLEU of 25.17. This represents a substantial relative improvement of over 27% compared to the prior best. The corresponding text BLEU of 31.95 also significantly surpasses previous results, underscoring the model’s robust capabilities.

Translation Fidelity Preserving speaker identity across languages remains challenging, which is why many prior S2ST systems restrict themselves to single-speaker synthesis. We assess cross-lingual speaker similarity for our zero-parallel model across FR/ES/DE→EN using a WavLM-based speaker verification model (Chen et al., 2022) (Table 2). Because the verifier is trained on monolingual data, cross-lingual evaluation inevitably suffers from language-mismatch effects, yielding lower absolute scores than monolingual settings. Even under this conservative regime, our model attains consistent similarity across all three language pairs and substantially outperforms the CVSS-T (Jia et al., 2022b) setting, indicating that our zero-parallel training effectively preserves speaker characteristics and prosodic cues in the translated speech.

	FR→EN	ES→EN	DE→EN	Avg.
CVSS-T	21.39	18.66	20.97	20.34
Ours (Unparalleled)	35.70	35.55	38.10	36.45

Table 2: Speaker similarity in cross-lingual speech translation on the CVSS test set under zero-shot setting.

4.5 Ablation Studies

Multi-stage training Our RosettaSpeech model is trained from the outset using a joint training

strategy, where data for speech-to-text translation (S2TT) and text-to-speech translation (T2ST) are mixed and learned simultaneously. To demonstrate the necessity of this approach, we conducted an ablation study comparing it against two sequential training methods, with results shown in Table 3. The sequential methods suffer from severe catastrophic forgetting. For instance, when the model is trained first on S2TT and then on T2ST, it forgets how to process speech inputs, causing its S2ST performance to plummet to a near-zero ASR-BLEU of 0.18. Conversely, training on T2ST first and then S2TT erases the model’s speech generation capabilities, resulting in an ASR-BLEU of just 0.49. In stark contrast, our joint training method avoids this issue, achieving strong and balanced performance across all four tasks.

	T → T	T → S	S → T	S → S
Ground Truth	-	84.52	-	-
Qwen3-0.6B	32.68	-	-	-
<i>Sequential Training</i>				
S2TT → T2ST	33.84	28.53	0.15	0.18
T2ST → S2TT	31.44	1.95	30.97	0.49
<i>Joint Training</i>				
S2TT + T2ST	34.14	29.27	31.78	27.86

Table 3: Translation performance on the CVSS-C (French to English) test set. **T** = Text, **S** = Speech.

Fine-tuning To further probe the capabilities of our framework, we explored the impact of fine-tuning the pre-trained RosettaSpeech model on a limited amount of parallel speech-to-speech data. As detailed in Table 1, this fine-tuning stage yields a substantial performance boost across all language pairs. For example, the ASR-BLEU score for French-to-English translation improves from 27.86 to 31.56, while the German-to-English score rises from 25.17 to 29.90. This demonstrates that our monolingual pre-training strategy creates a powerful foundation that can be rapidly and effectively specialized with even a small quantity of supervised data.

Furthermore, we investigated the model’s capacity for multilingual, many-to-one translation by fine-tuning a single model to handle French, Spanish, and German to English translation simultaneously. Remarkably, as shown in the final row of Table 1, this unified model maintains strong and competitive performance across all three language

pairs. This result underscores the scalability and efficiency of the RosettaSpeech architecture, proving its ability to support multiple translation directions within a single, compact model without significant performance trade-offs.

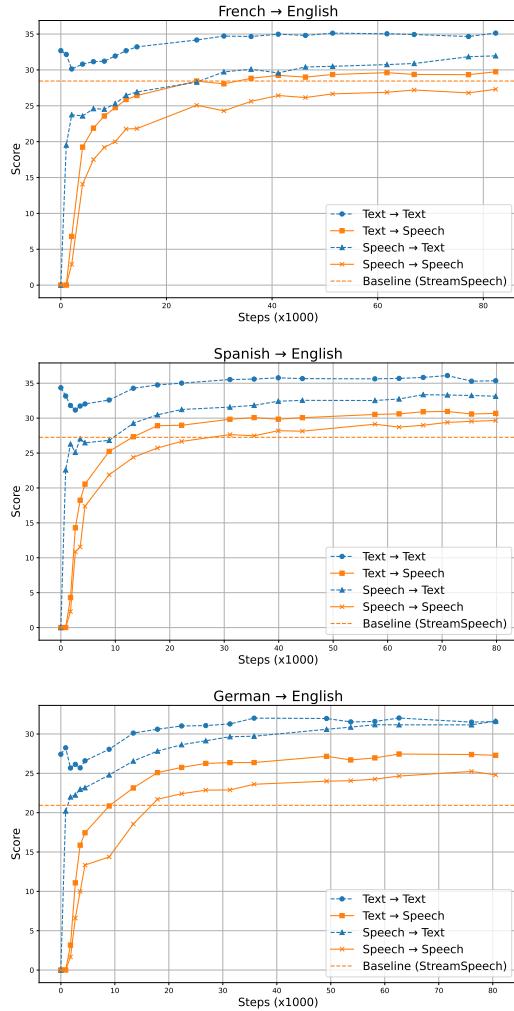


Figure 2: S2TT and S2ST results on the CVSS-C test set at different training steps, compared to the StreamSpeech baseline (the two dashed lines). From top to bottom are Fr→EN, Es→EN, and DE→EN respectively.

Training Steps and Data Scaling To provide a foundational understanding of RosettaSpeech’s behavior, we analyze its performance as a function of training steps and data volume.

Figure 2 illustrates the model’s performance on the CVSS-C test set at various training checkpoints for French, Spanish, and German-to-English translation. It is worth noting that at the very beginning of training, we observe a slight, initial dip in text-to-text translation performance. This phenomenon is expected, as the pre-trained text-only backbone is being adapted to handle more complex, multi-

modal objectives. However, as training progresses, this capability not only recovers but is further enhanced, leading to a clear and consistent trend: translation quality for all tasks—both text-output (Text→Text, Speech→Text) and speech-output (Text→Speech, Speech→Speech)—steadily improves with more training steps. Notably, our model surpasses the performance of the strong StreamSpeech baseline (indicated by the dashed orange line) relatively early in the training process, typically within the first 20,000 steps, highlighting its remarkable training efficiency.

Furthermore, we investigated the impact of data scale on final model performance for the FR→EN task. As shown in Figure 3, there is a strong, positive correlation between the amount of monolingual training data (measured in thousands of hours) and the resulting translation quality. Both the text-based BLEU and speech-based ASR-BLEU scores increase consistently as the data volume grows. Together, these experiments confirm that RosettaSpeech not only trains efficiently but also scales effectively with data. While limitations in computational resources and data availability for the source languages prevented a more exhaustive exploration of this scaling potential, our results demonstrate that the model already achieves a powerful level of performance even under the current constraints.

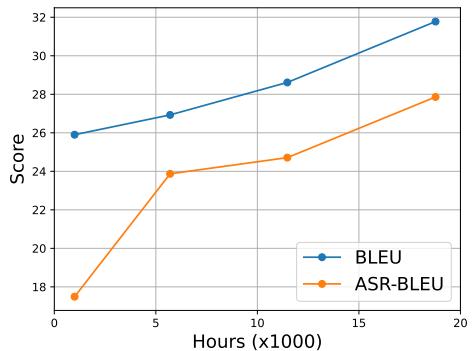


Figure 3: S2TT (BLEU) and S2ST (ASR-BLEU) results on the CVSS-C test set at different training data volume.

5 Conclusion

RosettaSpeech is a novel framework that achieves state-of-the-art, zero-shot speech-to-speech translation using only monolingual data. By leveraging text as an intermediate training bridge, our method bypasses the need for parallel speech corpora and demonstrates robust performance on standard benchmarks for French, Spanish, and German-

to-English translation. Ultimately, by removing this critical data dependency, RosettaSpeech provides a scalable and practical blueprint for extending high-fidelity speech translation to the vast number of languages currently underserved by technology.

Limitations

Despite RosettaSpeech demonstrates promising results, we acknowledge several limitations that present avenues for future research. Our current experiments are confined to translation from a few high-resource European languages into English, and extending the framework to a more diverse set of languages, especially low-resource ones, is a critical next step to assess its broader applicability. Furthermore, the models are currently designed for one-directional, many-to-one translation (into English); a more advanced implementation would support bidirectional or any-to-any translation for greater real-world utility. Our scaling analysis focused exclusively on the size of the training data. A valuable future direction, should sufficient computational resources become available, would be to explore the impact of scaling the model size itself. Finally, for true low-resource languages that lack even basic text translation systems (or where NMT quality is poor), the generated pseudo-labels may suffer from hallucinations or semantic errors, degrading the final S2ST performance. Therefore, our method is best suited for languages that are underserved in the speech domain but adequately supported in the text domain. Future work will investigate the minimum NMT performance threshold required for effective S2ST distillation and explore techniques to mitigate noise in NMT-generated targets.

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